Understanding Loneliness Through Data-Driven Approaches: From Practitioner Insights to Algorithmic Detection

Gregor Milligan

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Supervised by
Professor James Goulding
Professor Elvira Perez Vallejos
Dr Liz Dowthwaite

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Abstract

Loneliness can be both a cause and symptom of broader mental health concerns, in addition to having established negative impacts on physical health, employability and educational outcomes. This thesis examined the driving factors of loneliness through the lived experiences of lonely individuals and mental health practitioners. To achieve this understanding, the thesis employed a mixed-methods approach, combining thematic analysis of practitioner interviews, natural language processing (NLP) analysis of therapeutic transcripts, quantitative analysis of survey data and classification of forum posts through machine learning (ML) techniques.

The first empirical chapter consisted of semi-structured interviews with digital mental health practitioners, which revealed the hidden prevalence of loneliness concerns in digital therapeutic contexts. Despite loneliness affecting the majority of clients, the thematic analysis showed that practitioners consistently encounter almost exclusively indirect disclosures of loneliness due to the stigmatised nature of the concern. Practitioners identified subtle patterns of social disconnection rather than explicit statements of loneliness, highlighting a core challenge in clinical practice.

The second empirical chapter analysed 254 therapeutic transcripts using NLP methods and established a range of motivations that service users have for engaging in digital mental health interventions. Workshops with clinicians and service users led to the development of a validated 12-item outcome measure. Findings revealed the same indirect expression patterns that practitioners noted in the first empirical chapter, confirming both the latent nature of loneliness disclosures and their prevalence across digital therapeutic settings.

The third empirical chapter analysed survey data across London, United Kingdom (n = 2886), exploring the relationship between loneliness and stigmatised deprivation indicators, including food and energy insecurity. Hierarchical ML

modelling revealed that stigmatised deprivation significantly impacts loneliness beyond conventional socioeconomic measures, demonstrating that specific hardships create additional psychological burden independent of general income effects.

The final empirical chapter examined NLP detection methods for online loneliness disclosures. Traditional and contemporary NLP techniques were compared on labelled social media posts, while a systematic evaluation of data collection practices exposed critical methodological issues across the research domain. The results showed that high-performing classification models learn domain-specific linguistic patterns rather than genuine psychological indicators, revealing fundamental validity problems in current computational mental health research.

In conclusion, this thesis addresses critical gaps by revealing that loneliness is pervasive yet latent in therapeutic settings and that specific forms of deprivation create independent psychological impacts. Furthermore, computational detection methods can be susceptible to systematic data-confounding issues. These contributions have significant implications for both clinical practice and computational mental health research, while also establishing new frameworks for identifying loneliness and highlighting the need for rigorous methodological validation in the field.

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List of Publications

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2. **Milligan, G.**, Harvey, J., Dowthwaite, L., Vallejos, E. P., Nica-Avram, G., & Goulding, J. (2023). Assessing relative contribution of Environmental, Behavioural and Social factors on Life Satisfaction via mobile app data. 2023 IEEE International Conference on Big Data (BigData), Sorrento, Italy, 4186-4194. https://doi.org/10.1109/BigData59044.2023.10386740

3. **Milligan, G.**, Nica-Avram, G., Harvey, J., & Goulding, J. (2024). Food-insecurity.london: Developing a food-insecurity prevalence map for London—A machine learning from food-sharing footprints. International Journal of Population Data Science. https://doi.org/10.23889/ijpds.v9i4.2425

4. Semple, T., Rodrigues, L., Harvey, J., Figueredo, G., Nica-Avram, G., Gillott, M., **Milligan, G.**, & Goulding, J. (2024). An empirical critique of the low income low energy efficiency approach to measuring fuel poverty. Energy Policy, 186, 114014. https://doi.org/10.1016/j.enpol.2024.114014

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Chapter 1

Introduction

This chapter introduces the overarching structure of this thesis, including its theoretical motivations, aims, and research questions, and explains how these address specific gaps in loneliness research. It also provides an overview of the central contributions of this thesis.

1.1 Theoretical Motivations

Loneliness is defined as the subjective perception of a discrepancy between the desired and true social relationships in terms of companionship, connectivity, or intimacy (Hawkley & Cacioppo, 2010). It has been estimated that over 9 million people in the United Kingdom (UK) feel lonely either ***often or all the time*** (The Campaign to End Loneliness, 2023). Loneliness and its psychological impacts can affect anyone: the young or elderly (Lyyra et al., 2021; Tani et al., 2022; Wenger et al., 1996); those working full-time, part-time or the unemployed (Morrish & Medina-Lara, 2021; Segel-Karpas et al., 2018); those in varied household composition such as living alone or single parents (Nowland et al., 2021; Wenger et al., 1996); male, female and non-binary genders (Barreto et al., 2021; Schobin, 2022); those of differing sexual orientations (Gorczynski & Fasoli, 2022; Thunnissen et al., 2022); and people across a range of deprivation levels (Brunner et al., 2012; Elgar et al., 2021; NHS England, 2023; Office for National Statistics, 2023). The phenomenon transcends social boundaries and, according to the *Campaign to End Loneliness*(The Campaign to End Loneliness, 2023), in 2022, 49.63% of all adults in the UK (25.99 million people) reported feeling sometimes, often or always lonely, with 7.1% of the population experiencing loneliness ***all of the time***. The most recent data published by the UK's Office for National Statistics' *Public opinions and social trends, Great Britain: personal well-being and loneliness* August 2025 (Office for National Statistics, 2025), report that up to 51% of the population feel lonely some of the time and 6% all of the time.

This thesis delivers insight into the latent concern of loneliness through the lived experience of lonely individuals and mental health practitioners. Through four primary studies, this thesis provides an original contribution to the field of loneliness research by combining qualitative insights from mental health practitioners with rigorous analysis of survey and forum data from lonely individuals. This approach adds to the current research on loneliness, offering valuable insights to practitioners, and provides a detailed and novel understanding of loneliness.

1.2 Aims and Scope

This thesis addresses four research questions through corresponding research objectives that define the scope and methodology of the research.

1.2.1 Research Questions

1. How can digital mental health practitioners provide insight into loneliness in digital therapeutic contexts?

2. How are service user (SU) needs expressed in digital mental health interventions, and what methodological approaches can best capture them?

3. What are the social and economic drivers of loneliness, particularly in

relation to stigmatised lived-experiences?

4. To what extent can traditional Machine Learning (ML)and Large Language Models (LLMs) effectively identify loneliness self-disclosure in digital mental health forums?

To address these research questions, this thesis achieves four corresponding research objectives, which are enabled through appropriate methodological approaches and empirical investigations.

1.2.2 Research Objectives

1. To develop a comprehensive understanding of how loneliness is directly and indirectly expressed by clients in digital mental health settings through practitioner interviews.

2. To define and validate a novel single-session outcome measure that captures SUs' wants and needs, including those associated with loneliness.

3. To quantify the relative impact of stigmatised deprivation, social support, and environmental factors on loneliness using ML approaches.

4. To establish methodological approaches for detecting loneliness indicators in forum data.

1.3 Research Gap

This thesis addresses two primary research gaps:
1. Crucial contextual insight into loneliness disclosure in digital mental health platforms. Although there is work attempting to understand the disclosure of loneliness concerns in online forums such as X (formerly Twitter) and Reddit, the applicability of this work to mental health provision is limited, as the data being analysed often has no direct relation to the provision of mental healthcare. This thesis offers an understanding of how loneliness is discussed

in therapeutic contexts (Study 1) and mental health forum analysis (Study 4). The insights around mental health service delivery are grounded in study 2, which identifies a range of reasons a SU has engages in a digital mental health intervention, identifying experiences of latent loneliness which often manifest in indirect expressions such as wanting "To feel heard or understood" or "To build my support system".

2. Despite growing recognition of loneliness as a public health concern, there is limited research into how specific forms of deprivation, particularly those associated with stigma, contribute towards loneliness. Study 3 addresses this gap by identifying the unique impact of stigmatised deprivation on loneliness. This work demonstrates that the psychological experience of stigma associated with specific forms of hardship significantly influences loneliness in ways not captured by conventional socioeconomic indicators.

1.3.1 Methodological Opportunity

The increased adoption and implementation of ML approaches in mental health research, in place of established statistical methods, presents both opportunities and challenges. While these ML approaches offer novel insights, they require researchers to have a thorough understanding of their inner workings and the appropriate pre-processing steps that must be applied to the data before analysis is undertaken. Without this rigour, the spurious findings suggested by researchers can erode confidence in the outputs and findings for mental health practitioners, those implementing policy amendments, and the broader public. This creates both an opportunity for rigorous application to demonstrate appropriate use and the efficacy of these developing ML techniques in mental health research.

Particularly significant is the recent advancement in Natural Language Processing (NLP), driven primarily by the impact of the Transformer deep learning architecture, which has enabled the development of LLMs. These developments present a considerable methodological opportunity to understand the efficacy of LLMs in classifying mental health concern disclosures, such as loneliness, within therapeutic and other online contexts.

1.4 Central Contributions

This thesis presents a clear set of contributions which further the understanding of loneliness. The research encapsulates the lived experience of mental health practitioners, SUs and lonely people through a range of research outputs that shed light on loneliness. These research outputs include:

1. A suite of insights for practitioners which identify the nuances of loneliness disclosures online
2. An outcome measure for digital mental health practice, which is currently being used in a live mental health intervention
3. Novel insight into the unique driving effect of stigmatised deprivation on loneliness, contributing to research articles that further understanding of loneliness drivers
4. An analysis of the efficacy of different NLP approaches for detecting loneliness in text data generated on social media and digital mental health forums

This work also presents several novel methodological contributions to the broader computational social sciences:

- A hierarchical machine learning modelling approach was developed to understand the impact of key features, and to ascertain their incremental benefits in assisting the prediction of loneliness
- A framework for identifying dataset-induced confounding in social media datasets through feature ablation

- Identification of core principles for digital text-based data collection for classification studies

1.5 Thesis Structure

This PhD consists of four primary studies:

- Chapter 3 (Study 1): Loneliness from the Practitioners' Perspective

- Chapter 4 (Study 2): Developing a Digital Mental Health Outcome Measure - Understanding Service User Wants and Needs

- Chapter 5 (Study 3): Stigmatised Deprivation as a Driving Factor of Loneliness

- Chapter 6 (Study 4): Identifying Loneliness Self-disclosure in Online Forums

Figure 1.1 depicts the structure of the thesis and the interconnected nature of the chapters.

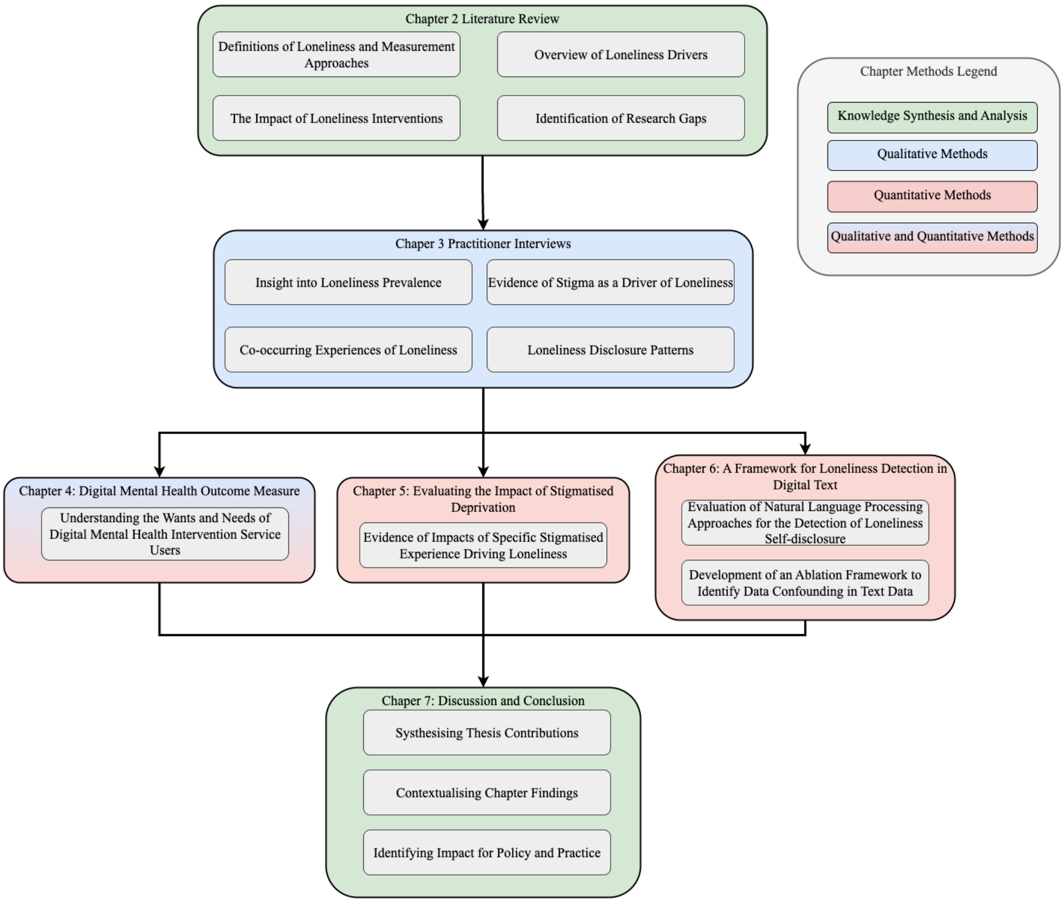

Figure 1.1: *Thesis Study Structure Overview*

1.5.1 Study 1: Loneliness from the Practitioners' Perspective

This study helps to identify how clients express concerns of loneliness in online therapeutic environments, providing insight into the prevalence of loneliness in digital mental health practice, the concerns and language used by clients to express loneliness. This work provides the theoretical underpinning which will contextualise the wider work included in the PhD.

Methods

A thematic analysis of 9 expert practitioner interviews with a range of specialisms (grief counselling, LGBTQ+ clients and children and young people) was undertaken. The thematic analysis revealed patterns and the themes exhibited by SUs co-occur with loneliness.

Findings

This work was able to document how shame and stigma are driving factors of loneliness. Some insightful quotes include: "In 6 years not one client has ever come straight and said 'I am lonely' and "Around 80% to 90% of my clients are facing loneliness in some way". Understanding how clients express themselves in therapeutic settings justified the development of the Adult Session Wants and Needs Outcome Measure (Adult SWAN-OM), the focus of study 2, ensuring the measure captures relevant dimensions of loneliness, including grief, stigma and social exclusion. Practitioner insights about stigma as a barrier to disclosure provided the theoretical foundation for investigating stigmatised deprivation in Study 3. Insight into how clients discuss loneliness was also revealed, primarily that clients discuss loneliness in an implicit manner and do not directly say "I am lonely" but rather use indirect language to describe how they feel.

Conclusion

Study 1 establishes both the need for and direction of the subsequent quantitative investigations of the way in which loneliness manifests (Study 3) and how clients discuss loneliness in digital mental health forums (Study 4) through the application of ML and NLP models.

1.5.2 Study 2: Digital Mental Health Outcome Measures - Understanding Service User Wants and Needs

Study 2 defines a novel single-session outcome measure (The Adult SWAN-OM) for digital mental health interventions. Building upon Study 1, which identified numerous reasons a SU could engage with a therapeutic intervention, Study 2 builds upon these insights by developing a systematic approach to capturing and measuring SU wants and needs through a concise single-session outcome measure.

Methods

The research employs a multi-phased approach combining NLP methods with the typical stages of outcome measure development as follows: (1) assumption definition and validation with SUs and clinicians; (2) transcript theme extraction using a LLM in conjunction with topic modelling to extract themes from 254 single-session transcripts from 192 SUs; (3) clinical item refinement focus groups; (4) content validity with clinicians and SUs to improve the relevance and clarity of the items; and (5) outcome measure finalisation in a workshop with clinicians.

Findings

Themes extracted from the analysis in Study 1 also validate how practitioner observations encapsulate a range of indirect loneliness expressions, for example “To feel heard or understood”, “To talk about my story or my concerns with someone who is not judgmental” or “To build my support system” which align with how lonely people may implicitly express their feelings of loneliness. The items in the SWAM-OM also link to stigmatised or shameful experiences such as “Help with grieving a loss” or “Learn how to become more accepting of myself” which were also identified by the practitioners in Study 1. 96 potential wants and needs were generated and distilled into 12 items. The outcome measure was shown to be relevant and clear to both SUs and clinicians when used in the context of a digital mental health intervention. Furthermore, SWAN-OM items encompass themes of enhancing social relationships and engaging in conversations without judgment, which are linked to strong social support and mitigating stigma, as identified in Study 3 as the most significant drivers of loneliness.

Conclusion

While the Adult SWAN-OM is not exclusively focused on loneliness, items within the measure directly relate to loneliness expressions. The measure provides clear intervention targets for practitioners that address the underlying drivers of loneliness. To conclude, Study 2 serves as a bridging study between Study 1 (understanding loneliness in therapeutic contexts) and Study 3 (identifying loneliness drivers) by capturing and measuring the ways SUs express needs that may signal loneliness.

1.5.3 Study 3: Stigma as a Driving Factor of Loneliness - Stigmatised Deprivation

Building on the practitioner insights from Study 1 and the measurement approach developed in Study 2, Study 3 examines the specific environmental and socioeconomic drivers of loneliness using a quantitative ML approach. This study introduces and explores the concept of "Stigmatised deprivation" - defined as forms of economic insecurity where individuals experience perceived social exclusion or shame when seeking support.

Methods

Through a survey of 2886 respondents across London, UK, this study employed a hierarchical ML approach using random forest models to identify the strongest predictors of loneliness. Data were collected on 21 variables spanning environmental factors (e.g., population density, access to transport, green spaces) and socioeconomic factors (e.g., income, food insecurity, energy insecurity, health status). Model Class Reliance analysis further confirmed the importance of these variables, demonstrating their explanatory power in predicting loneliness.

Findings

The findings revealed that after the inability to rely on friends and family, stigmatised deprivation, particularly food and energy insecurity, was the strongest predictor of loneliness. This relationship persisted even when controlling for income and general deprivation measures, suggesting that the stigma associated with specific forms of hardship has an independent psychological impact beyond financial hardship itself.

Conclusion

This study extended the qualitative insights from practitioners in Study 1 about the role of stigma in loneliness by providing quantitative evidence of its impact. It also complements Study 2's development of the SWAN-OM by identifying specific environmental and social factors that drive loneliness, many of which align with wants and needs captured in that measure ("To build my support system", "To feel heard or understood", "To talk about my story or my concerns with someone who is not judgmental").

1.5.4 Study 4: A Methodological Framework for Loneliness Detection in Digital Text

This chapter is comprised of two parts: **Part 1** applied a range of classification approaches to labelled test data pertaining to loneliness self-disclosure, evaluating the efficacy of traditional and contemporary approaches, highlighting the limitations of TF-IDF approaches for the prediction of mental health concerns across domains. **Part 2** identified a significant methodological flaw in the data collection approach of the original dataset, demonstrating how inadequate data collection processes can substantially undermine the real-world applicability of classification models.

Methods

Part 1 applied and compared traditional ML methods with contemporary LLMs to classify loneliness-related content in labelled forum text data. Part 2 conducted a systematic critique of the data collection methodology employed in the original dataset, identifying a significant flaw in its construction, which nullifies any insights gleaned.

Findings

The analysis revealed significant limitations of TF-IDF approaches for predicting mental health concerns across different domains, while demonstrating the superior performance of domain-enhanced language models. Additionally, the data collection analysis identifies critical weaknesses in the original data collection approach that potentially compromise the real-world applicability of computational mental health tools developed from such datasets. At the same time, it provides researchers with a framework to prevent and identify future data-confounding issues.

1.5.5 Conclusion

The results demonstrate that traditional NLP models achieved accuracy scores exceeding 93% on the Reddit dataset, whilst LLMs achieved 91% accuracy. These findings replicated the performance reported by Jiang et al. (2022); however, feature importance analysis revealed that models were learning spurious signals rather than genuine loneliness self-disclosure patterns. Critically, when tested on forum posts from Kooth (a digital mental health platform), both the traditional models and LLMs failed to generalise, indicating domain-specific overfitting rather than accurate loneliness self-disclosure detection. The ablation experiment conclusively demonstrated that dataset confounding was driving model performance, rather than detecting loneliness expressions, the models were primarily classifying which Reddit subforum posts originated from.

These findings reveal fundamental flaws in existing approaches to loneliness detection and underscore the crucial importance of rigorous dataset validation in mental health NLP applications.

Chapter 2

Literature Review

> *Until then I had always thought of loneliness as something negative—an absence of company, and, of course, something temporary. That day I had learned that it was much more. It was something which could press and oppress, could distort the ordinary and play tricks with the mind.* - John Wyndham: The Day of the Triffids (1957)

2.1 Introduction

As loneliness continues to permeate the everyday experience of millions of people (The Campaign to End Loneliness, 2023), there is an enduring necessity to understand both the lived experience of loneliness and contextual factors that contribute to this concern.

This literature review establishes the theoretical and empirical foundations necessary to understand loneliness as a psychological experience for the individual and as a broader public health concern. The chapter examines how different conceptual approaches to defining and measuring loneliness have informed our understanding of loneliness prevalence, before evaluating the driving factors of loneliness. The review concludes by assessing existing intervention approaches, identifying their limitations and positioning the contributions of this thesis within the broader landscape of loneliness research and therapeutic intervention.

The review addresses four core themes that provide the context for the four studies of this thesis. **First**, it examines how loneliness has been conceptualised and measured, establishing what constitutes loneliness and its related concepts and experiences, including stigma. **Second**, this review synthesises the prevalence of loneliness across the United Kingdom (UK) to understand who experiences loneliness and what drivers have been identified. **Third**, it evaluates data-driven approaches to identify more subtle drivers of loneliness, building on the currently established risk factors which drive loneliness. This third section also evaluates the affordances of Natural Language Processing (NLP) in providing insight through the analysis of therapeutic transcripts and digital text to understand how loneliness is expressed in both mental health intervention and broader digital contexts. **Fourth**, this chapter evaluates current intervention approaches for loneliness, highlighting the limitations of existing therapeutic frameworks for addressing loneliness and their associated criticisms, thereby justifying the need for the novel findings presented throughout this thesis.

This chapter provides context for the experience of loneliness through four overarching areas of review:

1. **Defining Loneliness**: Concentrating on providing an overview of varied definitions and conceptual models of loneliness, identifying the nuances of each and contextualising the range of loneliness experiences.

2. **Loneliness Prevalence Estimates and Measurement**: Synthesising prevalence estimates across demographic, socioeconomic, and geographic features in the UK while evaluating the measurement approaches that generate these estimates.

3. **Data Driven Approaches to Understand Loneliness**: Evaluating the individual and broader societal factors that contribute towards lone-

liness, and providing an overview of the affordances of data-driven approaches to provide more informed insight into the drivers of loneliness.

4. **The Success and Criticisms of Loneliness Interventions**: Evaluating the efficacy of traditional and digital therapeutic interventions, alongside policy and social prescribing responses for loneliness mitigation. This assessment positions the subsequent thesis findings and provides valuable insights for practitioners, researchers, and those who experience loneliness.

2.2 Loneliness Definitions and Conceptual Models

Loneliness is often defined as the subjective perception of a discrepancy between the desired and true social relationships in terms of companionship, connectivity, or intimacy (Hawkley & Cacioppo, 2010). Loneliness is typically perceived in two main forms:

- a unitary construct identified by differences in the actual and desired social relationships
- a multidimensional construct including both subjective experiences and objective social conditions

The UK Government (Department for Digital, Culture, Media and Sport, 2018) defines loneliness as "a subjective, unwelcome feeling of lack or loss of companionship", identified as a mismatch between the quantity and quality of social relationships that an individual has, and those that they want. This definition aligns with the views of Perlman and Peplau (1981) who defined loneliness as "a discrepancy between one's desired and achieved levels of social relations". Weiss represents this duality of the loneliness construct in his typology of loneliness (Weiss, 1975), in which loneliness is encapsulated in two forms. "Emotional loneliness" arises from the absence of emotional connections generated from intimate relationships and stems from the absence of an adequate social network; and "Social isolation", which can be caused by loss of a job, being excluded by peers or not belonging to a community. Direct *causes* of emotional loneliness include bereavement or divorce, while the *manifestations* of emotional loneliness include anxiety, a sense of "utter aloneness", and a tendency to misinterpret the affectionate intention of others.

Social relatedness is a key factor in reducing loneliness. If an individual does not have someone to consult with when they need advice and cannot count on the support of their friends and family, they are more likely to feel a sense of loneliness (Perlman & Peplau, 1981). Demographic characteristics, such as marital status, gender, and household composition, as well as descriptive characteristics of an individual's social network, such as the number and frequency of contacts with network members, and health, have been identified as factors that antagonise loneliness. Other factors which perpetuate loneliness, as identified by Jong-Gierveld and Tilburg (1999), include the ability or desire of an individual to adhere to social norms and values, internal expectations of support associated with certain relationships, and whether a social network meets the desired perceived quality.

2.2.1 Defining Loneliness Through the Lens of Measurement

There are several variations in the definition of loneliness (See Table 2.1); the nuance arises due to the conflation between the physical experience of social isolation and the subjective emotional experience of loneliness. There is, therefore, a need to identify said differences in each definition and acknowledge the distinct elements and nuances of loneliness. Perlman and Peplau (1981) provides a set of definitions that unpick the subtle differences between loneliness and social isolation based on Perlman's "Discrepancy Model" which posits that loneliness occurs when there is a significant mismatch or *discrepancy* between a person's *actual* social relations and their needed or *desired* social relations.

Term	**Definition**
Emotional Loneliness	The type of loneliness that occurs when a person lacks an intimate attachment figure, such as might be provided for children by their parents or for adults by a spouse or intimate friend
Loneliness	The subjective psychological discomfort people experience when their network of social relationships is significantly deficient in either quality or quantity
Social Isolation	The objective situation of being alone or lacking social relationships
Social Loneliness	The type of loneliness that occurs when a person lacks the sense of social integration or community involvement that might be provided by a network of friends, neighbours, or co-workers

Table 2.1: Definitions of Loneliness and Social Isolation from *Toward a Social Psychology of Loneliness* by Perlman and Peplau 1981 (Perlman & Peplau, 1981)

Each definition emphasises loneliness as a subjective experience by focusing on how a person feels about their social connections rather than objective circumstances (which is more typical for a definition of social isolation). This distinction highlights a core challenge of loneliness research, whereby one can feel lonely even when not completely socially isolated; the experience of loneliness is directly related to the perceived quality of social relationships and the sense of connectedness with others.

Although the overarching construct of loneliness is present across the preceding definitions, there are slight differences in the scope and focus of each as shown in Table 2.2. Townsend distinguishes between social isolation and loneliness as *objective* versus *subjective* experiences; loneliness is a subjective emotion opposed to social isolation's stark reality (Townsend, 1957). Weiss' typology distinguishes between social loneliness, arising from the absence of a broader social network, and emotional loneliness, stemming from the lack of intimate relationships (Weiss, 1975). Hawkley and Cacioppo (2010) crucially identify the "discrepancy" between desired and actual relationships while alluding to how this discrepancy could vary based on the subjective thresholds of the relationship type (companions or intimate relationships). Initial definitions describe a simple objective/subjective distinction by Townsend (1957), and more complex understandings developed based on the gap between desired and actual social relationships by Hawkley & Cappicio (Hawkley & Cacioppo, 2010).

Author, Year	**Paper Title**	**Defintion**
(Townsend, 1957)	The family life of old people	"Social isolation is objective, whereas loneliness is subjective; to be socially isolated is to have few contacts with family and within a community, and to be lonely is to have an unwelcome feeling of lack or loss of companionship"
(Perlman & Peplau, 1981)	Toward a social psychology of loneliness	"loneliness as a discrepancy between one's desired and achieved levels of social relations"
(de Jong Gierveld & Havens, 2004)	Cross-national comparisons of social isolation and loneliness: introduction and overview	"Feelings of loneliness involve a subjective evaluation related to a person's expectations of and satisfaction with the frequency and closeness of contacts"
(Hawkley & Cacioppo, 2010)	Loneliness Matters: A Theoretical and Empirical Review of Consequences and Mechanisms	"Loneliness is often defined as the subjective perception of a discrepancy between the desired and true social relationships in terms of companionship, connectivity, or intimacy"

Table 2.2: Definitions of Social Isolation and Loneliness in Literature

While these theoretical definitions establish the conceptual foundation for understanding loneliness, the operationalisation of these concepts sheds light on how loneliness manifests across populations. The difference between measurement frameworks, the implementation of *direct* versus *indirect* loneliness questions, and the audience the measure is designed for (specific demographics or broader populations) can influence the understanding of the severity and circumstances of who experiences loneliness. These measurement decisions define both research findings and policy responses to loneliness as a public health concern.

2.3 The Application of Loneliness Measures

As identified in chapter 1 individuals can experience loneliness in different ways, this nuance is exemplified when evaluating the differences in the conceptualisation of loneliness across a range of measurement instruments. Two frequently applied loneliness scales are the University of California, Los Angeles (UCLA) loneliness scale (D. Russell et al., 1978) and the De Jong Gierveld (DJG) Loneliness Scale (de Jong-Gierveld, 1987). Other scales include the Social and Emotional Loneliness Scale for Adults (SELSA) (DiTommaso & Spinner, 1993) and the Differential Loneliness Scale (DLS) (Schmidt & Sermat, 1983).

2.3.1 Direct Loneliness Measurement approaches

There are two main approaches to measuring loneliness, direct and indirect measurements. Direct measurement approaches are direct questions which ask the respondent to self-report their experience of loneliness. For example a single loneliness item asks respondents directly whether they felt lonely over the past week with the response options being yes and no (Shiovitz-Ezra & Ayalon, 2012). The ONS suggests that a direct measure of loneliness be included in surveys of loneliness along with indirect measures i.e. How often do you feel lonely? with the corresponding response options: Often/always, Some of the time, Occasionally, Hardly ever, Never (Office for National Statistics, 2018a). It is pertinent to note that given the stigmatised nature of loneliness, direct measurements must be evaluated with self-report bias in mind. Mund et al. (2022) identified that several studies have found under-reporting of loneliness using direct measures of loneliness vs. indirect measures of loneliness. A range of approach to mitigate and acknowledge stigma in loneliness measurement is provided in subsection 2.4.2.

Maes et al. (2019) identified that there was a significant difference in way in which different genders response to direct measures of loneliness, specifically finding that men reported lower levels of loneliness than women on direct measures of loneliness, whereas the sex difference on indirect measures of loneliness was non-significant. This difference in gender may also be reflected across different demographic features and highlight the need for a granular approach to loneliness measurement.

2.3.2 The University of California, Los Angeles Loneliness Scale

The UCLA scale focuses primarily on the "emotional experience" of social disconnection and considers loneliness to be a unidimensional construct that is rooted in the cognitive discrepancy model (Perlman & Peplau, 1981); in which subjective feelings of social isolation and dissatisfaction perpetuate an increased feeling of the perceived gap between desired and actual social relationships. The UCLA loneliness scale assumes that loneliness is experienced similarly across different populations, rather than considering context-specific elements of loneliness presented in the DJG loneliness scale.

The UCLA loneliness scale has undergone several iterations since the initial (Version 1) 1978 UCLA scale by D. Russell et al. (1978): The revised UCLA loneliness scale (R-UCLA)Version 2 (D. Russell et al., 1980) addressed the response bias identified during concurrent and discriminant validity testing. This bias was formed from the exclusively negative wording of the measurement items "I feel left out" or "I lack companionship" in which Version 2 incorporated both positively and negatively worded items such as "I have people I can talk to" while maintaining the 20-item structure; Version 3 D. Russell (1982) converted all 20 items from declarative statements to questions beginning with "How often do you feel...", for example "I lack companionship" to "*How often do you feel* that you lack companionship?" This addressed what

Russell identified as a "critical issue" in Version 2 of the scale, particularly regarding double negations and concerns about item clarity.

Several approaches have been proposed to define shorter forms of the 20-item UCLA and R-UCLA scales. Hughes et al. (2004) developed a shorter version of UCLA loneliness scale to enable large-scale population-based studies where questionnaire length constraints are often a concern. This three-item measure assesses feelings of a lack of companionship, feeling left out, and feeling isolated from others. A short form UCLA Scale, formed of 8 items by Hays and DiMatteo (1987), covers additional core contributors of loneliness such as having someone to turn to and the respondent's feelings of being withdrawn.

2.3.3 The De Jong Gierveld Loneliness Scale

The DJG loneliness scale is an 11-item measure that distinguishes between social and emotional loneliness by incorporating both objective and subjective aspects of social isolation into the scale. The scale considers loneliness to have distinct social and emotional components in which different types of relationships fulfil different psychological needs (such as close friends whom they can rely on, contented with the size of their social network, and frequency of experienced rejection) while accounting for the variation in experienced loneliness across cultural contexts through the use of positive items which assess desired relationships and social engagement. In contrast, negative items capture feelings of abandonment and a sense of missing relationships.

While loneliness can be experienced in two primary ways, emotional and social loneliness, the experience of loneliness contains further nuances, which become evident when comparing loneliness measurement scales (The UCLA Loneliness Scale and the DJG Loneliness Scale). These two scales exemplify different measurement philosophies. The UCLA scale conceptualises loneliness as a *unidimensional* construct reflecting the subjective experience of social disconnection, consistent with cognitive discrepancy theory. The DJG scale employs a *multidimensional* framework, explicitly distinguishing between emotional loneliness (the absence of intimate attachment) and social loneliness (the absence of broader social networks), thereby allowing for the examination of different loneliness dimensions across various contexts.

2.3.4 Other Loneliness Measures

Beyond the UCLA and DJG scales, several additional measures have emerged to address specific populations or measurement challenges, each reflecting distinct theoretical approaches to capturing the experience of loneliness.

The Differential Loneliness Scale

Developed by Schmidt and Sermat (1983), the Differential Loneliness Scale (DLS) represents a conceptual departure from preceding measures. Rather than treating loneliness as a global experience, the DLS is explicitly based on satisfaction within relationships and identifies specific relational domains where loneliness may manifest.

The DLS is a 60-item scale designed to measure the subjective sense of lacking satisfaction with a variety of social relationships. The relationships the scale deals with are: 1. romantic and sexual relationships, 2. friendships, 3. family relationships, .4. relationships with the community (Schmidt & Sermat, 1983). In particular, the scale attempts to measure the difference between what an individual's actual relationship is and the relationship they would like to have. Naturally, as the DLS comprises 60 items that focus specifically on relationships, the applicability of the scale differs from that of the broader R-UCLA or DJG Scales.

Social and Emotional Loneliness Scale for Adults

DiTommaso and Spinner (1993) developed the Social and Emotional Loneliness Scale for Adults (SELSA), comprising of three subscales measuring loneliness in romantic relationships (covering emotional loneliness), family relationships, and social relationships (social loneliness). Each subscale contains both positive and negative items to reduce response bias, following similar methodological approaches to the revised UCLA scales.

SELSA's three-part structure enables the more precise identification of relationship domains contributing to loneliness experiences, supporting the development of context-specific interventions. However, similarly to the DLS, its 37-item length and focus on *adult* relationship contexts limit its applicability in large-scale surveys or younger populations.

Children's Loneliness Scale

Children's Loneliness Scale (CLS) (also referred to as the Loneliness and Social Dissatisfaction Questionnaire), developed by Asher et al. (1984), covers items to identify loneliness in children, particularly contextualised within a school setting. Unlike the previously discussed, the CLS used direct questions of loneliness - item 21 is written "I am lonely". However, the CLS also used *filler* items which do not contribute to the outcome, such as item 2: "I like to read" to potentially mitigate some of the self-report bias generated when discussing concerns of loneliness.

The diversity of loneliness measures reflects different approaches to understanding the construct, ranging from unidimensional conceptualisations (UCLA) to multidimensional frameworks (DJG, SELSA) and relationship-specific measures (DLS). These scales have addressed various measurement challenges, such as subject appropriateness for the children taking the CLS. Despite this proliferation of measures, fundamental methodological and conceptual limitations persist across loneliness measurement.

2.3.5 Loneliness Measurement Criticism

Maes et al. (2022) discusses eight loneliness scales (including the scales discussed in this chapter), their conceptual underpinnings and broader limitations. Crucially, Maes et al. (2022) identifies how all the loneliness scales "*contained items that fail to reflect the subjective nature of loneliness*". Noting that the items "I have lots of friends" (CLS), "I am an outgoing person" (UCLA) or "It's easy for me to make new friends at school" (CLS) are related or predictive of loneliness to some extent, but do not *measure* loneliness. Rather, Maes' suggests that the focus of loneliness measurement should be to identify the actual discrepancy between desired and actual relationships.

The broader criticism concerns the UCLA and CLS' construction of loneliness as a unidimensional construct (Maes et al., 2022). This approach can minimise the multifaceted nature of loneliness experiences and could fail to capture meaningful distinctions between different types of loneliness. Some researchers also suggest that there are conceptual elements of loneliness which are missing from scales entirely, such as Gordy et al. (2022), who identified the need for the inclusion of a score of "neededness" which encapsulates the feeling to be desired or *needed* by someone as a construct of loneliness.

These limitations become particularly problematic when attempting to design targeted interventions, as the efficacy of the intervention may be hindered if the scale cannot distinguish between social versus emotional loneliness deficits or core constructs of loneliness that may require different therapeutic approaches. For example, in "Toward a Social Psychology of Loneliness" Townsend (1957), the authors describe the ways in which loneliness can be experienced across effective, cognitive, and behavioural manifestations of loneliness.

While longitudinal studies can be performed to understand loneliness temporally (Qualter et al., 2015), the scales do not have specific temporal measures, which, while subjective and susceptible to bias, could provide nuance to the studied phenomenon in cross-sectional studies. However, several Ecological

Momentary Assessment (EMA) studies have been undertaken to understand loneliness over time Terracciano et al. (2025), including in old age Badal et al. (2022) and Choi et al. (2025) or to understand how specific drivers such as mental health concerns Fittipaldi et al., 2024; Wolf et al., 2025, sleep Johnson et al. (2024) and Vacca et al. (2025), stress Kang et al. (2024).

Despite the methodological limitations and theoretical criticisms of loneliness measures, researchers and policymakers continue to attempt to quantify the prevalence of loneliness across populations. Understanding the pervasiveness and co-occurring patterns of loneliness remains crucial for informing public health policy, developing effective interventions for loneliness, and justifying the allocation of social resources.

2.4 On the Stigmatisation of Loneliness

Stigma has been defined by several researchers across disciplines and social contexts (Alonzo & Reynolds, 1995; Crocker, 1999; Link & Phelan, 2001; Manzo, 2004; Neves & Petersen, 2025), including for mental illness (Hinshaw, 2007; Link et al., 2004). The initial definition of stigma is credited to Goffman (1963) as "an attribute that is deeply discrediting" . Goffman's definition has been expanded upon a number of times, most relevant to the context of this literature review and the context of mental health research more broadly is the definition by E. Jones (1984) in which stigma is an attribute (a "mark") of an individual that is seen as an undesirable characteristic. Link and Phelan (2001) expands and refines the numerous definitions of stigma, identifying that stigma can only exist where there is a power asymmetry, identifying its four components:

1. **Labelling**: The social selection and identification of prominent human differences, where certain attributes are distinguished and labelled while the vast majority of human differences are ignored as socially irrelevant.

2. **Negative Stereotyping**: The linking of these labelled differences to undesirable characteristics, where dominant cultural beliefs connect labelled individuals to negative stereotypes.

3. **Separation**: The creation of distinct categories that accomplish the separation of "us" from "them", where labelled individuals are viewed as fundamentally different, thereby establishing social distance between groups.

4. **Status Loss and Discrimination**: The experience of a reduction in social hierarchies and unequal treatment, where labelled individuals face rejection, exclusion, and disadvantaged outcomes across multiple life domains.

2.4.1 Stigma as a Defining Facet of Loneliness

Weiss conceptualised the stigmatised element of loneliness stemming from the perception that it is a result of personal failing rather than being part of the human experience (Weiss, 1975). While this potential stigma is acknowledged in a study on the *Phenotype of Loneliness* by Cacioppo and Cacioppo (2012), the impact of stigma as a driver of loneliness remains minimally discussed. A 2025 paper by Neves and Petersen (2025) describes the social stigma of loneliness as remaining "under-theorised" despite its co-occurrence being noted by Robert Weiss Weiss (1975) as far back as 1975 and in the granular analysis undertaken by Barreto et al. (2022).

Stigma associated with loneliness can be further differentiated into two distinct manifestations, as described by Barreto et al. (2022): perceived stigma, which encompasses the broader public perception and social attitudes towards lonely individuals, and self-stigma, referring to the internalised shame and negative self-perceptions experienced by those who are lonely themselves. This dual manifestation of stigma represents a core element of the loneliness experience, wherein external social judgements become internalised, creating additional psychological burden beyond the loneliness itself.

Barreto et al. (2022) found differences in community and self-stigma across gender, with men having higher perceived community stigma, and women having higher self-stigma. Other demographic variations included younger people having higher loneliness self-report scores than older populations, and community composition contributing to experienced differences, with people living in collectivist countries perceiving loneliness as more controllable and experiencing more community stigma than people living in individualistic countries.

While these findings are insightful, Barreto et al. (2022) acknowledges limitations to their study, particularly around data composition, as not every sample across different countries was representative, and the survey did not account for individual definitions of loneliness, which may vary across cultures. Nevertheless, other studies consistently demonstrate that stigma has a mediating effect on loneliness across demographics, including age and gender (Z. Fan, Shi, Leng, et al., 2025; Hogerwerf & Suanet, 2025; Maes et al., 2019; Neves & Petersen, 2025; Prizeman et al., 2023; Rotenberg et al., 1997).

Lau and Gruen (1992) examined college students' perspectives of lonely and non-lonely people, finding that students did stigmatise those who were lonely. However, Kerr and Stanley (2021) argued that the questions used to determine social perceptions were confounded with social behaviours (such as "hasn't gone to any parties" or "pretty much keeps to himself"), potentially inflating stigma findings. Despite this methodological concern and the study's focus on a narrow demographic (college students), Lau's work is frequently cited, including by the UK government (Department for Digital, Culture, Media and Sport, 2018), to validate the stigmatised nature of loneliness.

Kerr and Stanley (2021) conducted several studies with both undergraduate and adult samples from the United States, finding that while undergraduates displayed high levels of stigmatising attitudes, there was no clear evidence that adults stigmatised lonely individuals, highlighting the need for further research into public perceptions of lonely people across different populations.

Given the substantial evidence for loneliness stigma across populations, and underlying evolutionary explanations suggesting that loneliness inherently carries shame to motivate reconnection with others (Cacioppo & Patrick, 2008), the question arises of how existing measurement approaches account for this stigmatised nature.

2.4.2 Accounting for Stigma in Loneliness Measurement

Ko et al. (2022) developed the 10-item Stigma of Loneliness Scale (SLS), which measures both **public** (identified by Barreto as community stigma) and **self**-stigma of loneliness. However, the scale has seen limited adoption since its development, with notable exceptions being the work of Zhiguang Fan, who developed a Chinese version of the SLS (Z. Fan, Shi, Luo, et al., 2025; Z. Fan et al., 2024) and conducted studies examining loneliness stigma in China (Z. Fan, Shi, Leng, et al., 2025).

SLS items related to self-stigma include: "If I were lonely, I would feel ashamed", "Being lonely would be embarrassing" and "Being lonely would mean there is something wrong with me". Public stigma items include: "Others would assume I am not good at talking to people if I were lonely", "Others would assume it is my fault if I were lonely" and "Others would assume I have not friends if I were lonely". Ko et al. (2022) found that those with higher loneliness scores would attribute more negative self-appraisals and self-isolate more when feeling lonely; and those who attribute greater stigma to loneliness would be less likely to disclose that they are lonely.

Loneliness measures are typically written using indirect language in an attempt to minimise the associated stigma, such as "How often do you feel that you lack companionship?" and "How often do you feel left out from others?" from the UCLA 3-item scale (Hughes et al., 2004), or "I often feel rejected" and "There are enough people I feel close to" from the DJG scale (de Jong-Gierveld, 1987), which does not directly mention loneliness. This lack of direct language may mediate some of the stigma associated with loneliness self-disclosure; however, the content may still contain concepts or experiences which are stigmatising, which should be considered when evaluating prevalence estimates of loneliness.

2.4.3 Loneliness Across Individualistic and Collectivist Social Environment

The nuance between individualistic and collectivist countries experience of loneliness warrents evaluation, particularly on the efficacy of measurement approaches in differing cultural contexts. Beller and Wagner (2020) identified that cultural individualism significantly moderated the effect of loneliness on health outcomes (such as physical and cognitive health); furthermore, the effect of loneliness on health became stronger in more collectivistic countries. A difference in the drivers of loneliness has been identified when taking into account the social environment of the individual, Lykes and Kemmelmeier (2014) found that in collectivist settings, family interaction was more closely linked to the experiences of loneliness than individualistic social contexts, identifying that the absence of interactions with friends and having a close social relationships was more indicative of loneliness for individualistic societies.

Contextualising this insight with the two most prevalent outcome measures (The UCLA and DGJ Loneliness scale), the UCLA scale was originally developed in the United States of America, a predominantly individualistic culture (D. W. Russell, 1996), where as the DJG scale has been specifically tested for cross-cultural equivalence and has established strong measurement invariance across various countries with different cultural contexts, including France, Germany, Russia, Bulgaria, Georgia, and Japan (De Jong Gierveld & Van Tilburg, 2010).

The different approaches to development and validation across scales presents a crucial consideration for researchers and policy makers. The measurements of loneliness undertaken in this thesis and broader contextualisation are seated within the UK which is a primarily individualistic nation, however, the findings of this thesis are still applicable to those who experience individual-level collectivism (i.e., perceiving the self or one's social environment as collectivistic) as described by Beller and Wagner (2020).

2.5 Loneliness Prevalence Estimates Across the United Kingdom

Evaluating the prevalence estimates of loneliness across the UK will elucidate loneliness geographically and also provide insight into the co-occurring experiences of lonely people. For example, the relationship between income, household composition or mental health conditions. This examination enables comparisons with other regional studies of loneliness to identify the factors that can be consistently associated with loneliness, and to develop specific survey studies that identify less commonly observed driving factors of loneliness.

The UK Government produced a range of reports showing the negative effects of loneliness across the population between 2018 and 2024 (Department for Digital, Culture, Media and Sport, 2018, 2023; Office for National Statistics, 2024; U. K., 2020, 2021, 2022). These reports show how loneliness has been linked to earlier deaths on a par with smoking or obesity, increased risk of coronary heart disease, stroke, depression, cognitive decline and an increased risk of Alzheimer's (Department for Digital, Culture, Media and Sport, 2018). However, loneliness research typically focuses on specific population subgroups, including university students, patients presenting at GP practices with comorbidities, and elderly residents in care homes (Altschul et al., 2021; Gerino et al., 2017; Reedman-Flint et al., 2022) which limit the insight that can be gleaned when compared to the analysis of loneliness across broader representative samples of the population.

The analysis of open access loneliness data from the Office for National Statistics (ONS), the UK's national statistical institute, enables comparison between theoretical literature on loneliness experiences and empirical population-level patterns. The ONS collects and publishes statistics on the economy, population, and society at national, regional, and local levels, including loneliness prevalence estimates. These estimates are gathered through rigorously selected population samples to ensure accuracy and enable comparisons across population subgroups, including those with mental health conditions (depression, anxiety), socioeconomic strata (Indices of Multiple Deprivation, income levels), and demographic categories (region, sex, age, physical health status).

For example, The "Public opinions and social trends, Great Britain: personal well-being and loneliness", a dataset published by the ONS, reports a range of social trends show a steady increase in self-reported loneliness over time (See Figure 2.1).

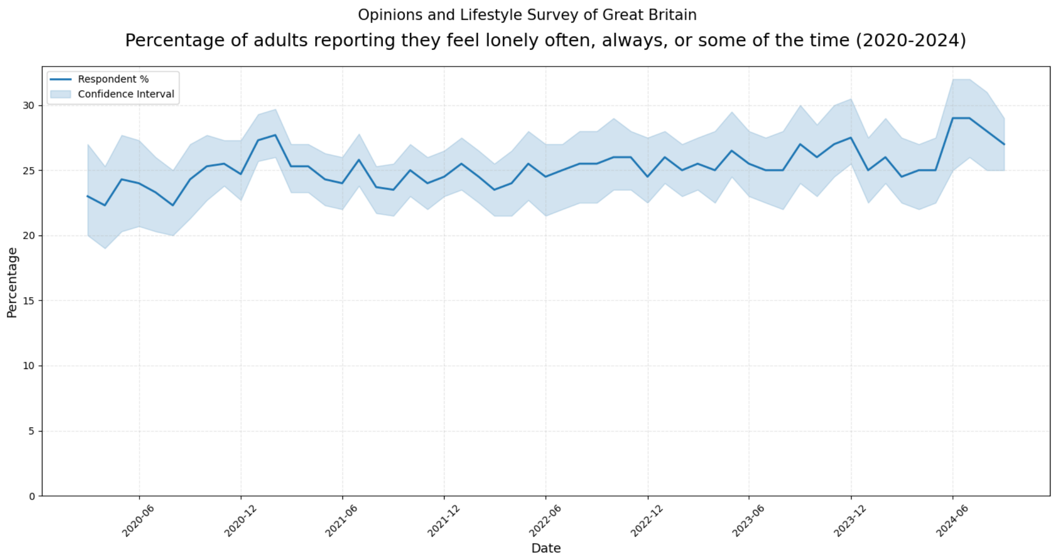

Figure 2.1: *Loneliness Prevalence Statistics Published in Public opinions and social trends, Great Britain: personal well-being and loneliness (October 2021 - September 2024)*

While there is a range of insights into the preclearance of loneliness published by the DMCS and ONS, there are still *evidence gaps* which have been identified in the most recent 2023 Tackling loneliness evidence review report (Department for Digital, Culture, Media and Sport, 2023). Particularly, it is unclear how specific demographic groups are impacted by loneliness, particularly stigmatised groups, such as LGBTQ+ or those with disabilities. Furthermore, further analysis of the impact of social, environmental, biological, and health factors on loneliness prevalence is suggested for future work.

2.5.1 Social Policy and Loneliness

Warham (1976) defined social policy as encompassing "*the actions of government that deliberately affect the distribution of resources, status, opportunities and life chances among social groups and categories of people within the country*".

The impact of social policy on loneliness experiences has been explored across a range of literature, however, this research typically focuses on older adults (Ghenţa & Matei, 2025; Nyqvist et al., 2019), reflecting the broader age bias present throughout loneliness research. However, Jentoft et al. (2025) notes that while there is limited robust evidence of social policy's impact on loneliness prevalence, this area remains relatively unexplored, suggesting that the relationship between policy interventions and loneliness outcomes among older adults requires further investigation.

It has been suggested that the steady increase in loneliness is in part due to the strong link between the quality of social policy and loneliness. Factors such as poor access to housing (Holding et al., 2020), transportation (Delbosc, 2012; Williams et al., 2024), limited access to green space (Astell-Burt et al., 2022) and increasing deprivation all contribute towards limiting social cohesion (S. Park & Berkowitz, 2024), combined with limited social support and weakened economic opportunities, which have a deleterious effect on experienced loneliness (J. Wang et al., 2018).

The specific characteristics of welfare institutions also increase the experience of loneliness, such as the quality and coverage of services and the general standard of living, health and wellbeing outcomes (Nyqvist et al., 2019). This relationship aligns with previous research linking welfare-institutional characteristics to broader health and wellbeing outcomes (Rostila, 2007; Rothstein & Stolle, 2003). Furthermore, extended waiting times to access healthcare across the UK, combined with increased private sector involvement across the NHS, particularly in mental health support and community care (Powell & Miller, 2016), should be noted when discussing the rise in mental health concerns, including loneliness.

This is particularly pertinent as social support and provision continue to stagnate and decline in the UK while mental health concerns persist and rise (Kung et al., 2022; Shields & Price, 2005), potentially contributing to increased loneliness prevalence. Supporting this concern, an online opinion poll conducted by YouGov for the British Red Cross in December 2022 (Scottish Government, 2023) revealed that 81% of Scottish respondents agreed that increased cost of living would make more people lonely, with 43% stating they would restrict socialising due to rising costs. In response to these challenges, Lawn et al. (2023) identifies three key policy-based approaches to reduce loneliness: first, improving access to high-quality health and social care with better loneliness identification, implementing social prescribing into routine care, and providing holistic support; second, building the volunteer support sector and expanding community-based support options; and third, recognising loneliness as both a health issue and a broader societal concern requiring coordinated response.

This overview highlights how social support provision is determined by government policy. Crucially, this enables governments to create potentially skewed metrics that determine eligibility for support, which can be used to minimise the support they are required to provide. Governments may achieve this by using poorly defined criteria or, in some cases, purposely obfuscating the true prevalence of social concerns.

For example, Semple et al. (2024) critiqued the UK Conservative government's metric for estimating energy insecurity, arguing that the total number of households defined as energy insecure was likely purposely minimised to reduce the number eligible for support. This approach serves two purposes, portraying to the public that the government is effectively managing energy precarity while simultaneously limiting financial obligations.

These concerns should be considered when evaluating approaches to measuring loneliness prevalence and assessing intervention success across the UK, particularly given the government's vested interest in demonstrating effective loneliness reduction strategies.

2.5.2 Deprivation and Loneliness

The relationship between loneliness and the quality of social infrastructures is a concern that the UK Government has acknowledged(Department for Digital, Culture, Media and Sport, 2023), finding the factors that contribute towards loneliness include physical health, deprivation and social care provisions. Therefore, understanding the relationship between deprivation and loneliness becomes crucial for policy consideration and development.

Deprivation manifests in various forms beyond a simple lack of income, with food insecurity and energy insecurity representing particularly relevant examples of how material hardship co-occurs with loneliness and feelings of social isolation.

Food insecurity creates multiple pathways to loneliness through both direct and indirect mechanisms. The financial constraints experienced by food-insecure individuals limit their ability to socialise, while the stigma associated with food insecurity can lead to social withdrawal (Stack & Meredith, 2018). Research demonstrates strong associations between food insecurity and mental health outcomes, with Elgar et al. (2021) noting that psychological consequences are particularly pronounced in contexts where food insecurity is less common and more stigmatised.

Similarly, energy insecurity, defined as the inability to meet basic household energy needs (Jenkins et al., 2016), demonstrates clear connections to social isolation. Multiple studies document the relationship between energy insecurity and increased anxiety, depression, and social stigma (Brunner et al., 2012; Hernández, 2016; A. Jones, Februray 2022). This shame associated with broader economic hardship creates additional barriers to social participation, potentially exacerbating existing conditions of social disadvantage.

While the UK Government has acknowledged this relationship. Given how deprivation can manifest itself in several ways, whether food and energy insecurity are present or not, a lack of income is not the only cause of deprivation, the consequences of an increased cost of living which enables this cycle of deteriorating physical and mental health. Burris et al. (2021) notes that quantitative analysis specifically examining these relationships remains limited.

A key gap remains in understanding whether deprivation-related loneliness represents symptoms of a broader psychological experience of material hardship, or whether specific forms of deprivation, particularly those carrying social stigma, hold distinct driving effects on loneliness independent of general socioeconomic status.

2.5.3 Loneliness and Covid-19

Research on the impact of COVID-19 on loneliness and broader mental health concerns continues to be published, with studies comparing pre-COVID and post-COVID periods (Henseke & Schoon, 2025; Nwabueze et al., 2025), despite the first UK lockdown beginning on 23rd March 2020.

It has been well established in the literature that social distancing measures and enforced lockdown (government-mandated restrictions on movement and social contact) had severe impacts on individuals' mental and physical wellbeing (Mansfield et al., 2021; Sansone-Pollock et al., 2025). The mental health impact was felt by a large swath of the population which may never have previously dealt with mental health concerns such as depression and anxiety (which is estimated, in some cases, to have increased by 27.88% and 26.35%

respectively) (Dettmann et al., 2022), while worsening already existing mental health concerns (Banks & Xu, 2020; Chatterjee et al., 2020; Pierce et al., 2020; Tsamakis et al., 2021).

Evaluating the changes in loneliness, a range of studies have examined the prevalence of loneliness before, during, and after the pandemic. Initial studies in 2020 suggested a minimal increase in loneliness from baseline measures. For example, Luchetti et al. (2020) reported that participants did not feel more isolated in response to the implementation of social distancing measures but did perceive an increased absence of social contacts during this initial stage of the outbreak.

This paradoxical effect of lockdown measures has been observed by several researchers (Bartrés-Faz et al., 2021; Bu et al., 2020). However, when examining longitudinal studies (Farrell et al., 2023; Rumas et al., 2021; Vaculíková & Hanková, 2023), loneliness was observed to be increasing, particularly among those who were either particularly at risk or had co-occurring mental health conditions. Bu et al. (2020) found that there was a slight increase in the most severe loneliness class and a decrease in the least severe loneliness class, and that a range of demographic, health, and social factors were related to the experience of loneliness rather than being directly related to the lockdown restrictions.

This apparent lack of an increase in loneliness is acknowledged by Killgore, Cloonan, Taylor, Lucas, and Dailey (2020) in a letter to the editor of Psychiatry Research, presenting findings that suggest that loneliness levels *did* increase during the first three and six months of the COVID-19 pandemic (Killgore, Cloonan, Taylor, Miller, & Dailey, 2020) and were significantly greater for those who continued to be restricted under lockdown rules.

The first prevalence estimates for the UK (in terms of accessible data from the ONS) show loneliness prevalence from October 2021 onwards (See Figure 5.1). However, a number of researchers argue that the impact of the pandemic will still be felt by those who experienced mental and emotional challenges, including loneliness, particularly at-risk groups such as students and young people (Malcom, 2021).

According to the ONS Public Opinions and Social Trends Report (July 2025) (Office for National Statistics, 2025), up to 28% of the British population report feeling sometimes, often or always lonely, with an estimated 8% feeling lonely all of the time. Table 2.3 shows the breakdown by age group and changes since 2021, with *young people* still being disproportionately impacted by feelings of loneliness.

Table 2.3: Loneliness prevalence by age group in Great Britain, 2021 (for National Statistics, 2021) vs 2025 (Office for National Statistics, 2025)

Age Group	Often/Always Lonely		Sometimes Lonely		Never Lonely	
	2021	2025	2021	2025	2021	2025
16-29	**7%**	**10%**	**26%**	**26%**	**33%**	**31%**
30-49	7%	6%	18%	21%	46%	44%
50-69	5%	5%	14%	16%	57%	56%
70+	3%	5%	10%	15%	65%	58%

While reports on COVID's impact on loneliness prevalence show mixed findings, with perhaps less severe population-wide increases than initially expected, the pandemic did disproportionately affect specific vulnerable groups. This differential impact, combined with increased public awareness of loneliness as a health concern, has highlighted gaps in existing support systems and the need for targeted intervention approaches.

2.6 Loneliness Intervention

The UK Royal College of Psychiatrists and British Geriatric Society (Society & of Psychiatrists London, 2019) have outlined several strategies for addressing loneliness, encompassing both clinical and societal approaches. These recommendations include enhancing access to quality health and social care services, developing better methods for identifying loneliness in clinical settings, and integrating social prescribing into comprehensive care pathways. The organisations also emphasise the importance of expanding volunteer networks and community-based support options while advocating for loneliness to be formally recognised as both a significant health concern and a broader societal challenge requiring coordinated intervention.

(O'Rourke et al., 2018) identifies strategies and interventions for reducing loneliness in older people. The most common type of loneliness strategy involved the lonely individual engaging in a "purposeful activity" and keeping busy such as engaging in community-based activities (such as volunteer work or joining clubs) that have the potential to bring them into contact with others or pursuing recreational activities which has also been acknowledged by other research in the reduction of loneliness (Andersson, 1985; Cattan et al., 2003; Pettigrew & Roberts, 2008).

There are some limited examples of successful community interventions that enable communities to engage via social prescribing (Department for Digital, Culture, Media and Sport, 2023), which were found to reduce feelings of social isolation and loneliness. The interventions suggested included befriending schemes which include scheduled personal contact with another person (Andrews et al., 2003; Cattan et al., 2011; Rook, 1984). Peer support groups were also identified in which participants attend meetings and select areas of discussion related to their needs and challenges, and peers and professionals provide information, resources and emotional support (Stewart et al., 2001). O'Rourke et al. (2018) also identified "reminiscence" as a form of loneliness intervention in which participants recall previous events or themes such as "*the old days*", "family histories" or "holiday traditions" (Chiang et al., 2010).

Alvarez et al. (2025) evaluates the effectiveness of social connection interventions for reducing loneliness and depression in young adults. Costello et al. (2022) demonstrates that participants engaging in *The Connection Project*, a relationship-focused intervention designed to enhance school belongingness and reduce symptoms of depression and loneliness among new college students. Those who engaged in this intervention experienced improved post-intervention belongingness compared to control participants, with students who attended more sessions reporting slightly greater gains in belongingness.

Charity Interventions and Support

There are also a range of charities within the UK that offer support for those experience loneliness. The Campaign to End Loneliness, is a national charity that works to create systemic change around loneliness through research, campaigning, and supporting organisations to develop evidence-based approaches; for example, cooking and food sharing initiatives[1]. Age UK, provides various services for older people experiencing loneliness, including telephone friendship service and local community activities. The Silver Line, offers a similar telephone helpline for older people, offering conversation, friendship, advice and practical support.

Loneliness cannot be addressed solely through social connection interventions, such as engaging in Activity Group Interventions or Strategies for Personal Development (Alvarez et al., 2025; O'Rourke et al., 2018; Zagic et al., 2022) as it is clear from the range of literature evaluated in this review that there are broader social issues driving loneliness. Nevertheless it is crucial to evaluate the impact of therapeutic approaches for reducing loneliness.

2.6.1 Therapeutic Approaches for Reducing Loneliness

When discussing interventions for loneliness, they are often contextualised within social and community activities. However, it is important to consider the efficacy of psychotherapeutic interventions in reducing loneliness. Hickin et al. (2021) evaluated the effectiveness of psychological interventions for loneliness. Intervention approaches included Interpersonal Psychotherapy (such as mental health education and tools to explore interpersonal relationships), with Cognitive Behavioural Therapy (CBT) being the most common intervention. Crucially Hickin et al. (2021) identifies that nearly all interventions

[1] I have personally participated in events with the Campaign to end loneliness, in which I joined a group in making and eating food together, which was both rewarding and insightful into the lived experience of and the approaches to mitigate loneliness.

have focused on older adults, which is also a common theme across loneliness literature review (Cacioppo et al., 2010; Hickin et al., 2021; Neves & Petersen, 2025; Penning et al., 2014; Perissinotto et al., 2012; Rook, 1984; Ruan et al., 2023). However, they do find that psychological interventions are effective at reducing loneliness and that future research should include those with lived experience of loneliness.

Imwinkelried et al. (2025) discusses the efficacy of psychological interventions for loneliness, identifying that they are effective, but a "one-size-fits-all" approach to address loneliness is highly unlikely to work given the nuanced contextual experience of loneliness. There is also the broader need for intervention to be accessible, as Imwinkelried et al. (2025) explained that addressing loneliness requires *not only* developing effective interventions but also ensuring they are available and accessible to diverse populations, which digital interventions may offer.

2.6.2 The Efficacy of Digital Interventions for Loneliness

The term digital mental health covers a range of digital modalities for online talking therapy to broader interventions.

There have been a number of studies evaluating different digital intervention approaches for reducing loneliness. Bruehlman-Senecal et al. (2020) evaluated the efficacy of the Nod app intervention for loneliness. However, it showed low engagement with participants not completing the required tasks proposed in the app (Alvarez et al., 2025).

Lehtimaki et al. (2021) evaluated the effectiveness of digital mental health interventions across clinical symptom targets such as wellbeing, anxiety or depression, but not loneliness, while also identifying that few studies have tracked the long-term efficacy and outcomes of digital mental health interventions. Borghouts et al. (2021) and Reinhard and Padberg (2025) discussed the barriers for users of digital mental health platforms with issues such as severe mental health issues, technical challenges, and a lack of personalisation, mitigating the potential benefits while also only identifying two studies which identified the efficacy of digital mental health intervention for loneliness (Jarvis et al., 2019; Lim et al., 2019).

Lim et al. (2019) proposed a digital intervention for loneliness (+Connect) which comprised of a 6-week programme of psychological content designed to improve relationship quality, suggesting that those with anxiety disorders *may* benefit from this intervention, given their small sample of 20 participants and the noted attrition of participants, their findings are limited. Allen (2020) published a commentary on the pilot study, acknowledging Lim's positive findings, also acknowledged limitations of the study, such as the need for young people to have access to smartphones and that previous loneliness research has suggested that technology may hinder social interaction more broadly Stepanikova et al., 2010.

There are specific types of intervention worth noting, such as self-guided online interventions for loneliness (Kaveladze et al., 2025), online CBT targeting loneliness in older people (Dworschak et al., 2024) and telephone-based interventions to target loneliness (amongst other mental health concerns) (Gilbody et al., 2024), showing the efficacy of a range of treatment approaches.

2.6.3 Policy Responses and Social Prescribing

It is clear from this literature analysis that loneliness cannot be addressed solely through conventional social connection interventions (such as engaging in *Activity Group Interventions* or *Strategies for Personal Development* (Alvarez et al., 2025; O'Rourke et al., 2018; Zagic et al., 2022)). Goldman et al. (2024) notes there is limited evidence found regarding funding for suggested interventions and that "policymakers can sustain the current momentum and strengthen their strategies by incorporating rigorous, evidence-based intervention evaluations and fostering international collaborations for knowledge sharing". However, given that government-led loneliness reports have not been published since 2023, the momentum and progress may have already been lost. Government-enabled social interventions are crucial, as there are limitations and criticisms of mental health interventions for addressing loneliness and social isolation (Akhter-Khan & Au, 2020; Balki et al., 2022). Primarily, the ineffectiveness of mental health support to reduce loneliness stems from the wide range of mechanisms that contribute towards loneliness, its cyclical nature and impact on/co-occurrence with other mental health concerns. Both "traditional" interventions (Talking therapy or CBT) and digital mental health interventions prove to be less effective for loneliness than for depression or anxiety (Allen, 2020; Hickin et al., 2021; Kumar et al., 2021).

Overall, this discussion of interventions highlights the limitations acknowledged across the literature for both community-based and psychotherapeutic interventions (Imwinkelried et al., 2025), underscoring the need for a deeper understanding of mental health practitioners' perceptions of loneliness to inform more effective intervention approaches.

2.7 Evaluating Loneliness Drivers through Data-Driven Approaches

Research has identified multiple drivers of loneliness, with Lim et al. (2020) identifying three core risk factors and correlates: *demography*, *health* (encompassing physical health, mental health, cognitive health, and genetics), and *socio-environmental* factors including digital communication and workplace contexts.

Furthermore, a plethora of research demonstrates that loneliness affects diverse populations, rather than isolated demographic groups. Loneliness impacts both the young and elderly (Lyyra et al., 2021; Tani et al., 2022; Wenger et al., 1996), those in full-time, part-time, or unemployed work situations (Morrish & Medina-Lara, 2021; Segel-Karpas et al., 2018), individuals across gender identities (Barreto et al., 2021; Schobin, 2022), and people of differing sexual orientations (Gorczynski & Fasoli, 2022; Thunnissen et al., 2022).

Given this contextual nuance in loneliness experiences, appropriate methodological approaches should be applied to data pertaining to the loneliness lived experience to understand how these diverse features drive loneliness outcomes. Machine learning (ML) models can enable a broader understanding of how features impact and contribute to the experience of loneliness compared to qualitative approaches for understanding loneliness, which rely on methods such as interviews (Fardghassemi & Joffe, 2022; Macdonald et al., 2018) and often have limited sample sizes or specific contextual boundaries.

A range of ML and statistical studies have been undertaken to evaluate loneliness quantitatively. Several studies have applied machine learning approaches to identify key predictors of loneliness across different populations.

Ejlskov et al. (2018) used Random Forest methods to understand relationships between 49 features and loneliness in individuals aged 68 or above, finding that positive wellbeing, an absence of health problems and being married were strong predictors of lower loneliness.

Altschul et al. (2021) applied gradient-boosted modelling to understand differences in predictors of loneliness between two age groups (45-69 and 70-79 years), finding that emotional stability and household composition (living alone) contributed towards experiences of loneliness.

Other studies have used traditional statistical approaches to examine loneliness relationships. Kearns et al. (2015) applied multinomial linear regression on cross-sectional survey data to understand loneliness and deprivation, finding that feelings of social connectedness and the ability to rely on family and friends reduce feelings of loneliness, while stressors such as deprivation, crime rates and poor governmental social support increased experiences of loneliness. Structural equation modelling (SEM) has been applied to show the relationship between stress and loneliness to be bi-directional over time (Laustsen et al., 2024), while Gerino et al. (2017) found loneliness influences mental health and physical quality of life in Italian adults aged 65-90.

A range of data streams can be evaluated to understand loneliness. Methods involve the statistical analysis of self-reported survey data, and text data analysis methods to evaluate disclosures of loneliness. Typically, these text data are generated on social media platforms such as X (previously Twitter) or Reddit (Andy, 2021; Guntuku et al., 2019; Koh & Liew, 2022; Ng et al., 2023). Other data streams include sensing technologies, such as smartphones, Fitbit, and Bluetooth data (Doryab et al., 2019; Site, Lohan, et al., 2022; Site, Vasudevan, et al., 2022; C. Wu et al., 2021).

2.7.1 The Specific Affordances of Natural Language Processing for Loneliness Understanding

While the previous section has covered the affordance of self-reported survey and sensing data, text data can offer a granular insight into understanding the self-disclosure of loneliness and the context surrounding the concern.

In the context of broader mental health concerns, NLP has been employed for a wide range of applications, from understanding general wellbeing, for example, predicting satisfaction with life by applying topic modelling techniques to Facebook message transcripts (Schwartz et al., 2016) or estimating the wellbeing of populations using tweets (Jaidka et al., 2020). Examples of NLP use cases for specific mental health concerns include recognising schizophrenia, detecting suicide ideation from counselling transcripts, and analysing social media data to detect depressive symptoms (Althoff et al., 2016b; Coppersmith et al., 2018; Oseguera et al., 2017; Strous et al., 2009). (Cook et al., 2016) showed that NLP models can generate relatively accurate predictions in identifying individuals at risk of psychological distress or suicide by using answers from a simple questionnaire about the patient's mood.

Several studies have evaluated therapeutic transcripts to identify recurring themes and model topics (Althoff et al., 2016a; Milligan et al., 2024a; Sridhar et al., 2021). Studies have also focused on the classification of specific mental health concerns (Jackson et al., 2017; Ryu et al., 2021). This work is often focused on depression (Arachchige et al., 2021; Yadav & Sharma, 2023), anxiety (Teferra & Rose, 2023) and suicide ideation (Li et al., 2023; Oseguera et al., 2017) with limited research into loneliness.

Recent advances in NLP, notably the proliferation of large language models (LLMs), offer new possibilities for more sophisticated detection approaches (Sun et al., 2024; Xu et al., 2024). However, their application to loneliness remains unexplored. The research engaging with LLMs for loneliness research is primarily contextualised as conversational agents to "reduce" feelings of loneliness rather than classification or conceptualisation (Shahid et al., 2025; Wynter, 2025).

The application of NLP for loneliness understanding is often contextualised around older people. For example, to evaluate whether language used by older people differs based on loneliness status (Badal, Graham, et al., 2021; Badal, Nebeker, et al., 2021; N. Wang et al., 2024), as well as to analyse care notes of older lonely people (Rickman et al., 2025). However, the most prominent area of loneliness analysis through NLP is achieved through the analysis of social media data, due to its prevalence and ease of access compared to private electronic health care record data and therapeutic transcripts. Additionally, the analysis of therapeutic transcripts is often evaluated through qualitative methods (Verity et al., 2024) rather than NLP approaches.

Understanding Loneliness Via Social Media Text Data

While the analysis of social media posts is common, there are very few labelled datasets pertaining to the self-disclosure of experiences of loneliness. Typically, NLP analysis involves unsupervised clustering of posts to enable the modelling of topics in a corpus of tweets, rather than classifying posts into lonely or non-lonely categories.

Several studies have applied topic modelling approaches to understand loneliness discourse on social media. Ng et al. (2023) conducted unsupervised learning of longitudinal Twitter data between 1st January 2012 and 1st September 2022, noting the impact of COVID, technology and loneliness portrayal in the media, and highlighting the multifaceted nature of loneliness and its contextual nature. Similarly, Andy (2021) applied topic modelling and Linguistic Inquiry Word Count (LIWC) to evaluate loneliness topics across different subreddits, finding that users often seek advice about socialising, improving communication and relationships.

COVID-19 provided a specific context for loneliness research, with Koh and Liew (2022) examining how loneliness was being discussed during the pandemic. They identified three main themes: the limited ability to socialise, causing loneliness, the impact of social distancing on loneliness, and the impact of loneliness on mental health, demonstrating how topic modelling can be used to identify common experiences of loneliness in social media data.

Other studies have focused on prediction and classification approaches. Guntuku et al. (2019) evaluated tweets between 2012 and 2016, identifying users whose Twitter posts contained the words “lonely” or “alone” and comparing them to a control group who did not tweet these keywords. They applied topic modelling and LIWC approaches to identify associations between loneliness and linguistic markers of mental health, finding they could predict whether a post was eliciting loneliness concerns with 86% accuracy using features derived from topic modelling and LIWC analysis.

While these insights are useful in contextualising the lived experience of loneliness, without adequate ground truth data, that is, data which has been labelled using an appropriate loneliness taxonomy with the assistance of appropriately trained psychologists, psychotherapists or counsellors, the ability to infer more nuanced insights from lonely and non-lonely individuals from social media data remains limited.

Limitations of Loneliness NLP Research

Jiang et al. (2022) explains that annotated social media datasets, rather than datasets gathered through keyword-based data scraping, can prevent prediction bias for keywords when training text classifiers, further suggesting that labelled data enables the capture of a broader range of loneliness expressions. There are granular approaches to labelling loneliness self-disclosure within text data, particularly Kivran-Swaine et al. (2014)'s framework which identifies how loneliness is disclosed in online contexts: including 1. temporal bounding, 2. context of the expressed loneliness (social, physical or romantic loneliness), and 3. explicit interactivity within the expression (seeking advice, providing support or reaching out for support). However, the application of such frameworks remains limited, and current data collection approaches present additional methodological concerns. Rather than using a framework Garg et al. (2023) labelled a dataset of Reddit posts based on whether their content matched the overarching themes of three prominent loneliness measurements (The R-UCLA, DGJ and LDS Scales).

Studies such as Kiritchenko et al. (2020) and Guntuku et al. (2019) rely on data collection methods that capture only direct use of terms related to loneliness (lonely, alone), missing potential linguistic patterns and contextual cues that signal loneliness indirectly. These limitations align with Chancellor and De Choudhury (2020)'s broader critique of mental health research in computational social science, in which they identified "concerning" trends regarding construct validity and methodological rigour in how researchers operationalise and identify mental health conditions. Primarily, the language features used in data collection approaches, combined with the limited capture of demographic information, restrict understanding of how loneliness manifests across different populations and contexts. These limitations raise questions about generalisability to clinical contexts and whether enhanced contextual understanding of loneliness can translate into effective intervention approaches.

2.8 Summary and Research Question Alignment

This literature review provides the broader context for the specific studies undertaken in this thesis. The initial part of this review examines the nuanced definitions of loneliness, highlighting both their conceptual differences and similarities. The core element of loneliness is a lack of quality connections and a discrepancy between desired and actual social connections. While specific literature is covered more granularly in each study chapter, this review contextualises the defined research questions in Chapter 1 section 1.2. Several key insights emerge from this synthesis. These insights reveal critical gaps in the current understanding of loneliness that warrant systematic investigation. The following sections examine how each research question addresses these limitations.

2.8.1 Key Insights and Identified Gaps

Measurement approaches to loneliness demonstrate important differences in the framing of loneliness across various contexts. Prevalence data reveal a steady increase in loneliness since the ONS began consistently measuring loneliness; however, there is a concerning trend in which the UK government has made loneliness less of a policy priority, evidenced by the lack of recent publications of the "Tackling Loneliness Annual Report". The broader impacts of stigma have been established, though further work understanding specific forms of deprivation could be undertaken to better understand this relationship. Additionally, ML approaches show promise in understanding the nuanced drivers of loneliness, but there are limitations in terms of the data being captured, particularly regarding the impact of specific stigmatising effects and the availability of properly labelled text data. These insights reveal critical gaps in the current understanding of loneliness that warrant systematic investigation.

2.8.2 Practitioner Insights for Loneliness Intervention

A range of loneliness interventions has been subject to various criticisms, particularly regarding the efficacy of both social and therapeutic interventions. There is insufficient understanding of how loneliness manifests and is expressed in digital therapeutic settings, as well as how this might differ from traditional face-to-face therapeutic contexts. Question 1 (***How can digital mental health practitioners provide insight into loneliness in digital therapeutic contexts?***) aims to address this limitation by providing contextual insight from practitioners on the contextual nature of loneliness and its disclosure, which can directly inform loneliness interventions.

2.8.3 The Impact of Stigma and Deprivation

This review also established the impact of both stigma and deprivation as an instigator of loneliness. However, existing analyses of the lived experience of loneliness inadequately capture the impact of nuanced forms of stigmatised experiences and the specific drivers that contribute to loneliness, rather than just using coarse demographics. Question 3 (***What are the social and economic drivers of loneliness, particularly in relation to stigma-***

tised lived-experiences?) addresses this gap by evaluating specific forms of stigmatised deprivations and contextualises the impact through the national prevalence estimates and the indirect consequence of weakening social policy, which leads to deprivation.

2.8.4 The Affordance of NLP Approaches

NLP methods can offer specific insights into loneliness but are limited due to the lack of labelled data, the use of social media can limit the applicability of findings to practice and the unsupervised nature of the majority of research outputs. This limitation is addressed across two research questions. Question 2: ***How are service user needs expressed in digital mental health interventions, and what methodological approaches can best capture them?*** is contextualised through the broader analysis of mental health intervention transcript data, to evaluate unsupervised ML approaches to evaluate service user needs across a large number of transcripts, contextualising the prevalence of the broader needs of services users and identify the efficacy computational approaches in captures theses concerns.

Question 4: ***To what extent can traditional ML and LLMs effectively identify loneliness self-disclosure in digital mental health forums?*** specifically targets loneliness through the analysis of a labelled lonely dataset enabling the evaluation of traditional and contemporary supervised ML approaches and enabling the employment of explainablity tools to understand the indicators of loneliness self-disclosure in text posts evaluating both social media and mental health forum post data.

These identified gaps necessitate a mixed-methods approach that combines qualitative insights from practitioners with quantitative analysis of survey and text data to gain a more nuanced understanding of loneliness. The integration of practitioner interviews, computational analysis of therapeutic transcripts, and ML approaches to survey data enables both the qualitative understanding and quantitative validation required to address these interconnected limitations and knowledge gaps.

This thesis addresses these gaps through four systematic studies that collectively advance both the theoretical understanding of loneliness and the practical applications of digital mental health interventions. The following chapter presents the first of these studies, examining loneliness from practitioners' perspectives in digital therapeutic contexts.

Chapter 3

Loneliness from the Practitioners' Perspective

Abstract

Background

Loneliness is a prevalent and growing concern across the United Kingdom. While numerous validated scales exist to quantify the severity and prevalence of loneliness experiences across populations (UCLA Loneliness Scale and the DJG Loneliness Scale)(de Jong-Gierveld, 1987; D. W. Russell, 1996), there remains a gap in understanding how loneliness manifests and is addressed within therapeutic practice. Given the associated stigma and shame surrounding loneliness disclosure, practitioner perspectives offer crucial insights into how clients express loneliness concerns within digital therapeutic environments.

Objectives

The objectives of this chapter are to gather the practitioners' perspective of loneliness within a digital therapeutic context, and are defined as follows:

1. To understand how practitioners identify loneliness concerns

2. To identify how loneliness is elicited in digital mental health interventions

3. To identify co-occurring themes (such as grief, shame, and social disconnection) that signal loneliness concerns in client communications within digital therapeutic environments

Methods

Semi-structured interviews were conducted with nine experienced practitioners (minimum one year of practice). Participants included specialists in grief counselling, LGBTQ+ support and digital mental health platform therapists. Interview transcripts were analysed using Braun and Clarke's six-phase thematic analysis approach, employing an inductive, data-driven methodology to allow themes to emerge from participant accounts rather than fitting data to pre-existing theoretical frameworks.

Results

Four interconnected themes were identified: 1. Conceptualising Loneliness: practitioners distinguished between social contact and meaningful connection, identifying the experience of being "*lonely in the crowd*" where clients feel disconnected despite having social networks; 2. Contextual Causes: loneliness emerges from life transitions (university, grief, relationships change), stigmatised identities and cultural minorities (LGBTQ+, neurodiversity), and resource reduction (youth services closures and social support); 3. Expressions and Language: specifically that clients rarely expressed loneliness directly, instead using terms like "*depressed*" or "*misunderstood*", with disclosure patterns varying by age and stigma experience; 4. Mental Health Co-occurrence: severe mental health conditions created bidirectional cycles where loneliness exacerbated symptoms, while mental health difficulties increased social isolation. Practitioners reported that 80-90% of their clients experienced loneliness concerns, yet direct disclosure was virtually absent across all participants' experiences.

Conclusion

Practitioners identified multiple stigmatising experiences as contextual drivers of loneliness, highlighting how loneliness emerges not only from individual factors but from broader patterns of social exclusion and marginalisation. For therapeutic practice, these insights suggest that practitioners can use awareness of stigmatising experiences as potential indicators when assessing loneliness risk. The presence of these contextual patterns were consistent across digital and traditional therapeutic environments previously identified in the literature, providing a foundation to develop more targeted interventions that address both the emotional experience of loneliness and its underlying social drivers across therapeutic environments.

3.1 Introduction

Loneliness is a growing concern in the United Kingdom (UK), with its prevalence increasing year over year (Office for National Statistics, 2024). The Campaign to End Loneliness published data showing 49.63% of UK adults report feeling lonely often or sometimes (The Campaign to End Loneliness, 2023). This prevalence is also seen at an international level, with 40% of older adults in the United States of America reporting feeling lonely (Perissinotto et al., 2012) and 37.9% for Chinese adults aged over 50 (Ruan et al., 2023). Understanding loneliness at an individual level is particularly pertinent as loneliness demonstrates bidirectional relationships with other mental health concerns (Caple et al., 2023), whereby loneliness both increases vulnerability to mental health difficulties and emerges as a consequence of them.

While numerous validated scales exist to quantify loneliness experiences across populations (e.g., UCLA Loneliness Scale and the DJG Loneliness Scale) (de Jong-Gierveld, 1987; D. W. Russell, 1996), there remains limited research examining how loneliness manifests within therapeutic practice from practitioners' perspectives, particularly in digital mental health contexts, despite the increasing uptake of online therapeutic interventions.

Given the established relationship between loneliness and co-occurring mental health conditions (Lim et al., 2020; Ludwig et al., 2022), and the interpersonal stigma that may affect therapeutic disclosure (Barreto et al., 2022; Reupert et al., 2021), understanding how experienced practitioners identify and interpret loneliness presentations is crucial for informing therapeutic practice and intervention approaches.

With the advent of digital mental health interventions and online therapy, those in need have more ready access to cost-effective and context-appropriate therapy. Online interventions can be broad or targeted in terms of the concerns they aim to address, with numerous services for anxiety, depression and suicide prevention (Balcombe & De Leo, 2023; Braciszewski, 2021; Iorfino et al., 2019). There are also broader interventions such as Internet-based Cognitive Behavioural Therapy (Schueller & Torous, 2020) or text-based talking therapies that focus on broader outcomes (Milligan et al., 2024b).

As digital mental health platforms become increasingly prominent points of therapeutic contact, questions arise about how loneliness manifests and is communicated within these environments. Practitioners working in digital therapeutic contexts may observe distinct patterns in how clients express loneliness through text-based interactions, or alternatively, loneliness expression may remain consistent across therapeutic modalities. Understanding practitioners' perspectives from these digital environments provides an opportunity to examine loneliness disclosure patterns in contemporary therapeutic practice and explore how interpersonal stigma operates within online therapeutic relationships.

This study focuses on the practitioner insights through a thematic analysis (TA) of experienced practitioners across digital therapeutic practice. This study's aims are the following:

1. To understand how practitioners identify loneliness concerns

2. To identify how loneliness is elicited in digital mental health interventions

3. To identify co-occurring themes (such as grief, shame, and social disconnection) that signal loneliness concerns in client communications within digital therapeutic environments

The completion of these aims enables the answering of the question: *How can digital mental health practitioners provide insight into loneliness in digital therapeutic contexts?* and achieve the research objective 1 to *develop a comprehensive understanding of how loneliness is directly and indirectly expressed by clients in digital mental health settings through practitioner interviews*

3.2 Background

The growth of digital mental health interventions has created a substantial cohort of practitioners with extensive experience in identifying and responding to loneliness concerns across diverse client populations. Practitioners occupy a unique observational position in loneliness research. While individual clients may experience loneliness in isolation, practitioners encounter multiple cases over time, enabling them to identify patterns in disclosure, recognise co-occurring themes, and observe the varied ways loneliness manifests in therapeutic contexts. This accumulated clinical expertise represents a valuable but underexplored data source for understanding how loneliness is expressed, experienced, and addressed in contemporary therapeutic practice.

While there is a range of quantitative elucidations into the co-occurring factors of loneliness (Davis et al., 2023; C. Park et al., 2020), qualitative evidence can offer a range of nuanced experiences that even the lengthiest loneliness survey or measure cannot achieve due to the individual's inability to describe their own lived experience.

3.2.1 Qualitative Insights into Loneliness

There have been a number of qualitative studies into the experience of loneliness; however, they are primarily from the perspective of the lonely individual. Such studies are often contextualised across a specific demographic characteristic, such as gender or age (Qualter et al., 2015). Although there are nuances across these demographics, similar trends have emerged regarding the importance of connectedness (Hawkley & Cacioppo, 2010). Studies have shown a U-shaped distribution, indicating that younger and older individuals experience loneliness more frequently than those in middle age (Hawkley, 2022; Qualter et al., 2015; Victor & Yang, 2012).

Qualitative research has found a range of consistent experiences that can be used to identify the core characteristics of loneliness. K. E. Martin et al. (2014)

interviewed 33 adolescents (aged 10-15) stratified by socioeconomic areas, finding that the young people identified two core elements defining their loneliness experience: 1. Connectedness with friends, and 2. Perceptions of "*aloneness*". Fardghassemi and Joffe (2022) used a free association technique and TA with 48 young adults (aged 18-24) from the four most deprived boroughs of London, identifying five key themes explaining the subjective causes of loneliness: 1. **The Feeling of Being Disconnected**, arising from feeling one does not matter, is not understood, or is unable to express oneself; 2. **Contemporary Culture**, relating to social media and materialism; 3. **Pressure**, associated with finding work or friends; 4. **Social Comparison**, such as feeling behind in life, and 5. **Transitions Between Life Stages**, including the breakdown of relationships, loss of significant others, and transitions in education or employment.

Another characteristic of loneliness is its hyper-contextual nature and relationship with co-occurring facets of the individual's lived experiences. For example, Verity et al. (2021) evaluates how young people conceptualise loneliness across age ranges through qualitative interviews with 24 young people ages 8-14. They found that young people conceptualise loneliness differently in different contexts, such as the experience of loneliness at school compared to loneliness at home. Verity et al. (2021) also reinforced the idea that loneliness cannot be attributed to a single cause but varies across the sample, such as change (moving to a new place or a new school) or social exclusion from peer groups, causing increased loneliness.

It is clear that social disconnection and comparison are present across different age groups and study contexts. Both studies Fardghassemi and Joffe (2022) and K. E. Martin et al. (2014) highlight that loneliness fundamentally stems from a perceived lack of meaningful connection with others rather than just being alone. This suggests that regardless of specific demographic characteristics or qualitative methodological approaches, the core loneliness experience centres on unmet needs for meaningful social connections. While these contextual concerns do offer some consistency into loneliness, stigma serves as a significant overarching experience of an individual's lived experience, which can directly exacerbate feelings of loneliness.

Loneliness and the Impact of Stigmatised Experiences

Stigma is of particular note as it leads to challenges in both social and therapeutic environments in which an individual may not be as open to discussing a concern due to the stigmatised nature of either the antagonist of loneliness or loneliness itself. Barreto et al. (2022) analysed loneliness and the associated stigma across a range of determinants, finding that the stigma *of* loneliness significantly affects disclosure patterns, with one third of UK respondents reporting they would be embarrassed to admit feeling lonely, and quantitative loneliness measures producing higher scores when avoiding direct loneliness terminology. Their research demonstrated that stigma drives concealment behaviours, with women more likely to report shame when experiencing loneliness, while men perceived greater community stigma around loneliness, providing empirical support for why clients might avoid direct loneliness expression in therapeutic settings. There is an established link between the experience of shame and loneliness (Barry, 1962; Cooper, 2024). The way in which mental health concerns are discussed in the media also contributes towards their general stigmatisation (Paton et al., 2024) as they are seen to be negative experiences, as Klin and Lemish (2008) describes the way in which the mental ill are presented in the media as "*peculiar*" "*different*", but also as "*dangerous*". Providing a narrative which perpetuates sensationalised and stigmatising characterisations (Zhang & Firdaus, 2024).

Crucially, it has been established that those who experience loneliness feel shame because they are lonely; Dahlberg (2007) evaluates interviews with participants aged between 11 and 82 who describe the experience of loneliness as "*Shameful*" and "*Ugly*". Loneliness can perpetuate from feelings of shame (rather than only causing shameful feelings) for those who have been othered in some way (Reupert et al., 2021), such as those who experience rejection and neglect from peers, as feeling particularly stigmatised (Asher & Wheeler, 1985; Barreto et al., 2022; Cooper, 2024). Madsen et al. (2021) conducted 15 semi-structured, individual interviews with eighth-grade adolescents (aged 14–15 years) who were immigrants, descendants, or had a Danish majority background, finding that loneliness was often described as a challenging feeling that varied in intensity and duration. Crucially, participants in Madsen et al. (2021) characterised loneliness as an "*invisible social stigma*" in which loneliness itself is a stigmatised experience.

The relationship between immigration and loneliness is complex and can be experienced at any age (Madsen et al., 2021; Z. Wu & Penning, 2015). The broader challenge of immigration in terms of social adjustment is identified across a range of cultural contexts (Ponizovsky & Ritsner, 2004; Salari et al., 2025). Immigration leads to a myriad of persistent instigators of loneliness, particularly due to the contextual nature of the immigration experience, such as employment opportunities, language barriers, loss of established social networks, and cultural adaptation challenges (Kirova, 2001; Xiong & Xu, 2023).

Mental health is a stigmatised experience which often co-occurs with loneliness (Abplanalp et al., 2024; Mann et al., 2022; Mushtaq, 2014) and understanding the relationship between this specific stigmatised preexistence and loneliness is particularly critical.

Loneliness Co-occurrence with Mental Health Concerns

The idea of being "othered" is a factor in the experience of mental health concerns; in turn, those who experience significant or severe mental health episodes, such as psychosis, are often lonely due to this isolating experience and the stigma around the concern (Gasull-Molinera et al., 2024; Ludwig et al., 2022; Mushtaq, 2014). There is an established relationship between loneliness and mental health concerns. Birken et al. (2023) interviewed people who had self-reported mental health concerns to establish connections between loneliness and mental health. They identify four core themes: 1. What the word "*lonely*" meant to participants, 2. Connections between loneliness and mental health, 3.Contributory factors to continuing loneliness, and 4. Ways of reducing loneliness, identifying the contributory factors to continuing loneliness and approaches for reducing loneliness.

While there are overlaps between loneliness and depression (Cacioppo et al., 2010; van Winkel et al., 2017), understanding how practitioners differentiate these experiences in clinical practice requires observations of the specific ways clients express loneliness concerns within therapeutic environments. While individual lived experience remains crucial for understanding loneliness, practitioners' perspectives offer a unique viewpoint, as their exposure to multiple loneliness presentations enables them to identify patterns that may not be apparent from individual accounts alone.

3.2.2 Practitioners' Perspectives on Loneliness

Without practice-based insight from practitioners, the way in which loneliness is expressed and the experiences therein remain opaque. However, few qualitative interview studies with practitioners have been undertaken.

Stefanidou et al. (2021) interviewed 20 mental health practitioners who focus on first-episode psychosis in the UK; the majority of service users with early psychosis experience feelings of loneliness. They often encountered socially isolated and disconnected clients, believing them to be lonely, but service users rarely discussed loneliness explicitly in clinical interactions.

Dobarrio-Sanz et al. (2021) interviewed 26 healthcare professionals about their perceptions of loneliness in older adults, identifying that loneliness is highly contextual and should be taken more seriously as a public health concern. Verity et al. (2024) analysed online counselling conversations between Childline counsellors and adolescents. Young people often employed short-term coping strategies that distracted them from loneliness. Issues with trusting others and self-worth acted as barriers to seeking long-term help. They identified five core themes: 1. Loneliness as an Extreme, Dark Experience; 2. Exhausted by Loneliness, But Unable to Sleep Restfully; 3. Loneliness Centred Around Difficulties With Peer Relationships, Which Was Made Worse by Conflict at Home; 4. School as a Difficult Place to be while Experiencing Loneliness; 5. Belief That Coping Strategies Fail to Alleviate Loneliness.

This reinforces the consistent pattern across studies that loneliness fundamentally centres on peer relationship quality and social environmental pressures, regardless of age group or other demographic experience.

While not specifically mental health practitioners, Jovicic and McPherson (2020) interviewed General Practitioners (GPs), finding that those experiencing loneliness visit their GP more frequently than those who are not, which has the potential to put a strain on GP and health support waiting lists while also increasing costs; they also determined that loneliness co-occurs with with physical and mental health conditions while also affecting cognition and lifestyle.

while there are consistent themes around connectedness and stigma which emerge from studies with both individuals and practitioners, which enable the understanding of contextual drivers of loneliness, there are limitations in the range of studies available. As shown above, practitioner insights are rarely examined; however, when they are, they reveal a range of ways in which individuals experience loneliness (Dobarrio-Sanz et al., 2021; Lawn et al., 2023; Stefanidou et al., 2021). For example, there is specific language used by those who experience loneliness and disclose it to practitioners. Understanding the language used to disclose loneliness can provide practitioners with context into when a client is expressing loneliness and offer some understanding of the nuances of the experience. The study described in this chapter addresses the gap in limited practitioner-based conceptualisation, in which practitioners describe their experiences of engaging with clients in a range of contexts and provide much-needed elucidation and evidence on the concern of loneliness in therapeutic practice.

There is a diverse range of contextual elements that make individuals lonely, which can lead to a range of nuanced emotions. Verity et al. (2021) found that young people described a discrete set of emotions to characterise the experience of loneliness, including "*sadness*", "*anger*", "*emptiness*", "*feeling unloved*", and "*hopeless*", which are comparable to those provided by adults (Heu et al., 2021; Perlman & Peplau, 1981; D. Russell et al., 1978). Practitioners tend to have a plethora of experience of the range of ways in which loneliness is expressed; using practitioner expertise to identify the themes which are most commonly present in the loneliness experience enables a broader understanding of the nuances involved.

Practitioners can also observe longitudinal patterns and changes across treatment periods, providing contextualisation into the challenges that individual client interviews might overlook. This opportunity to recognise patterns across cases represents an opportunity to provide understanding of loneliness, which is unavailable through studies of single instances of loneliness.

While this preceding body of work (summarised in Table 3.1) demonstrates the co-occurring themes based on practitioner expertise, there remains very limited qualitative research focusing specifically on practitioners within digital mental health interventions. This is a notable gap given the growing uptake of online mental health support, and the unique ways in which loneliness might be expressed and addressed in digital contexts. The present study addresses this gap by examining how digital mental health practitioners perceive and respond to loneliness in their practice.

This study will consist of a set of semi-structured interviews with practitioners to understand their perceptions of loneliness and provide critical real-world insight into how practitioners tackle issues of loneliness within online therapeutic practice and digital mental health intervention.

Table 3.1: Summary of Practitioner Interviews: Loneliness in Healthcare and Mental Health Settings

Citation	**Setting / Country**	**Participants**	**Method**	**Key Findings**
Stefanidou et al. (2021)	Early Intervention Services for first-episode psychosis, UK	20 mental health practitioners (multidisciplinary team)	Semi-structured interviews	Loneliness common in service users; linked to isolation and disconnection; rarely discussed explicitly in sessions
Dobarrio-Sanz et al. (2021)	Healthcare for older adults, Spain	26 healthcare professionals (nurses, physicians, psychologists)	Interviews and focus groups	Loneliness perceived as highly contextual; under-recognised; requires public health focus
Jovicic and McPherson (2020)	Primary care, UK	19 General Practitioners	Semi-structured interviews	Loneliness linked to higher GP visits; co-occurs with mental/physical conditions; impacts cognition and lifestyle
Lawn et al. (2023)	Mental health services, Australia	322 survey respondents (consumers, carers, practitioners)	Survey (mixed sample; limited practitioner-specific reporting)	Loneliness linked to stigma, judgement, and lack of safe spaces; practitioner perspectives not clearly separated
Verity et al. (2024)	Childline online counselling, UK	Childline counsellors (analysis of transcripts)	Qualitative TA of chat transcripts	Five themes, 12 subthemes; young people use short-term coping strategies; trust and self-worth key barriers
Present Study	Digital mental health platforms, UK	9 digital mental health practitioners (grief counselling, LGBTQ+ specialists, platform moderators)	Semi-structured interviews with TA	80-90% prevalence; indirect expression only; stigma as barrier; contextual causes; co-occurrence with mental health conditions

3.3 Methods

TA of practitioner interviews was selected as the methodological approach, as it enables a granular view of loneliness across digital practice. Therefore, practitioners who practice digitally were recruited to answer a series of questions about their clients' experience of loneliness. The scope of the questions (as described in section 3.3.2) focused on practitioners' experiences and perceptions of loneliness among their service users.

3.3.1 Dataset

Ethical approval for this study was granted by the University of Nottingham Business School (Application ID 202324037). The practitioner participants provided written informed consent when participating in the conducted interviews.

Participants and Recruitment Procedure

Nine practitioners with a minimum of one year of practice were recruited from a range of digital mental health practice contexts to gather an understanding of the nuances of loneliness across mental health practice intervention approaches. Table 3.2 shows the distribution of practitioners across platforms, demographic and professional characteristics.

Table 3.2: Participant Demographics and Professional Characteristics (n = 9)

Participant	**Gender**	**Age**	**Professional Role**	**Platform**
P1	Female	71	Grief Therapist (Psychodynamic)	Assoc. for Online Therapists & Remote-based therapy
P2	Female	40	Emotional Wellbeing Practitioner	Kooth
P3	Not reported	–	Emotional Wellbeing Practitioner	Kooth
P4	Male	38	DBT Therapist & Supervisor	Assoc. for Online Therapists & Remote-based therapy
P5	Female	52	Counsellor & Mental Health Mentor	Assoc. for Online Therapists & Remote-based therapy
P6	Female	–	Emotional Wellbeing Practitioner	Kooth
P7	Female	59	Psychotherapist	Assoc. for Online Therapists & Remote-based therapy
P8	Male	41	Wellbeing Moderator	Togetherall
P9	Female	37	Mental Health Nurse and Wellbeing Practitioner	Togetherall

Note: All participants identified as White British except P3 and P6 (not reported)

Overview of Digital Intervention Platforms and Counselling Associations Recruited From

Kooth

Kooth is a UK-based digital mental health service commissioned by the National Health Service (NHS), local authorities, and third-sector organisations. It provides free, confidential, and anonymous support to children, young people, and adults. The platform combines asynchronous features (e.g., mood tracking, psychoeducational content, peer forums) with synchronous text-based counselling delivered by qualified practitioners. Access does not require referral, and there are no waiting lists, which positions it as an early-access intervention within public health provision.

Togetherall

Togetherall is a peer-to-peer, digital mental health platform accessible 24/7 and designed to offer anonymous support through community interaction. Membership is typically provided via institutions such as universities, healthcare systems, or employers, and may be free or subsidised depending on the provider.

The Association for Counselling and Therapy Online

The Association for Counselling and Therapy Online (ACTO) is a UK professional membership organisation that sets ethical and competency standards for practitioners delivering therapy remotely. ACTO maintains a directory of accredited online therapists, provides specialist training guidance, and publishes professional frameworks for safe and effective online practice. It functions as both a regulatory reference point and a professional support network for practitioners working in digital contexts.

3.3.2 Materials and Procedures

Semi-structured interviews were conducted using questions based on established literature to gain specific insights into the lived experience of loneliness and the language often used when disclosing concerns about loneliness.

Interview Questions

The questions were as follows:

1. How would you define loneliness?
2. How prevalent is the issue/concern of loneliness in your experience working with [Their Platform/digital therapeutic environment]?
3. What is your experience working with young people who experience loneliness?
4. What words and phrases are typically used when talking about loneliness in this context?
5. What are the challenges around loneliness that your clients experience?

3.3.3 Analysis Approach

TA is an iterative method employed to evaluate qualitative data (Ibrahim, 2012). Through TA, interview content was classified into broad themes, primarily driven by predefined interview questions. However, the semi-structured nature of the interviews allowed the interviewer and practitioners to discuss tangential yet conceptually related themes that emerged as the interview progressed. These themes were refined as the interviews were conducted, enabling the researcher to identify the point at which saturation of relevant opinions appeared to occur. Analysis employed an inductive, data-driven approach, allowing themes to emerge from participants' accounts rather than fitting data into pre-existing theoretical frameworks.

Data saturation was approached pragmatically, recognising that complete theoretical saturation is rarely achievable in qualitative research (Saunders et al., 2018). After nine interviews, the core thematic structure had been established, with no new primary themes emerging.

TA is performed following the six-phase approach outlined by Braun and Clarke (2006):

1. Familiarisation and Re-familiarisation with the data: There was already a baseline of familiarisation with the transcripts, as the researcher was also the interviewer. Due to the imprecise nature of the automatically generated transcriptions captured via Teams, the recordings were re-listened to, allowing the transcripts to be corrected and refamiliarising the researcher with the interview content.

2. Generation of initial codes: The interview transcripts were classified using codes, and new codes were generated if appropriate to encapsulate a new concept. During the first pass through the interviews, the coding process was systematic yet flexible, allowing for the introduction of new concepts from each transcript. This was accomplished through the use of NVivo 15, a tool used to evaluate transcripts and generate codes across a corpus.

3. Establishment of Core Themes: After being generated, codes were collated into initial themes to be further analysed and evaluated.

4. Review of themes: An analysis of established themes was undertaken to identify gaps and overlaps across the themes. Overarching themes and sub-themes were identified. Some themes were merged where overlap was present, while others were split to better capture distinct concepts.

5. Naming and definition of themes: The final themes were defined based on their overarching content and given appropriate names.

6. Report production: To support the reporting of the results, compelling examples were extracted to illustrate the themes identified in this analysis. The themes are discussed and contextualised with the other identified themes to generate conclusions about the findings.

3.4 Qualitative Results

The TA of the 9 semi-structured interview transcripts revealed several interconnected themes related to the experience of loneliness. Based on transcript coding, four core themes were identified: 1. Conceptualising Loneliness; 2. Contextual Factors and Causes of Loneliness; 3. The Expressions and Language of Loneliness; and 4. The Co-occurrence of Loneliness and Mental Health Concerns. These themes directly address the research aims to understand how practitioners identify loneliness, its prevalence and manifestations in digital mental health interventions, and the expressions and co-occurring concerns that signal loneliness.

3.4.1 Theme 1: Conceptualising loneliness

This theme captures the ways in which loneliness is conceptualised by practitioners, identifying a lack of connection with others as a fundamental component of loneliness. Practitioner 3 defined loneliness as "*a feeling of wanting connection but having that not be fulfilled for some reason or another*". This idea of connection to others helps to differentiate loneliness from social isolation, in which someone can be connected with others but still feel lonely. It was further established that connections must be meaningful and supportive, as Practitioner 9 described loneliness as

> "The absence of support and meaningful connection [...] No one understands who you truly are like the core self."

This highlights how loneliness is not just based on social experience but rather as an unmet social need, a crucial distinction that emerged across the interviews.

The need for meaningful connection is demonstrated by Practitioner 4, identifying the typical expression of loneliness: "*I don't feel like anyone understands me or I don't feel like they are my actual friends*". This indicates how an individual can have a social group with whom they engage, but without what

Table 3.3: Overview of Core Themes and Subthemes

Core Theme	**Subtheme**	**Description**
1. Practitioners Conceptualising Loneliness	Loneliness is a lack of meaningful connection with others	How practitioners define loneliness in terms of unmet connection and the quality of interpersonal relationships
	Loneliness vs Solitude	Practitioners' distinction between chosen solitude and unwanted isolation
	The significant prevalence of loneliness	Practitioners' observations regarding the pervasiveness nature of loneliness
2. Contextual Factors and Causes of Loneliness	Transition, Loss and Loneliness	How life transitions and bereavement contribute to loneliness experiences
	Loneliness through Stigma and Social Barriers	The role of stigma, discrimination, and social exclusion in creating and perpetuating loneliness
	The impact of the reduction in social resources and the increased cost of living	How economic pressures and reduced social infrastructure contribute to loneliness
3. The Expressions and Language of Loneliness	Indirect expressions of loneliness	How service users communicate loneliness concerns without explicit disclosure
	Age-related differences in loneliness expression	Variations in how different age groups articulate and present loneliness concerns
4. The Co-occurrence of Loneliness and Mental Health Concerns	Pathways to severe mental health issues	How loneliness contributes to the development or exacerbation of mental health conditions
	Loneliness as a consequence of specific mental health concerns	How certain mental health conditions create or intensify experiences of loneliness

they perceive to be a meaningful connection. Practitioner 3 highlights a core challenge for those experiencing loneliness: "*No one's doing anything wrong, but they still just don't quite connect*". This presents a challenge for both clients and practitioners in identifying clear contributing factors because it suggests loneliness can occur even in ostensibly functional relationships, making it difficult to attribute loneliness to specific relationship problems or social circumstances.

This feeling of belonging and connection with others is fundamental to the nature of loneliness as it drives feelings of shame and further stigmatises the struggle. Practitioner 7 identifies the impact of shame of disclosure:

> "Often loneliness is a word I think people don't always want to use. There's an element of shame. Especially if they've got lots of friends, like, why do I feel lonely?"

When relationships appear functional yet a meaningful connection remains absent, clients may experience shame about their loneliness, questioning why they feel isolated despite having social relationships.

Loneliness vs Solitude

An important distinction emerged between loneliness and solitude; while loneliness was characterised as a negative experience, Practitioner 2 described expressions of comfort in solitude:

> "There's a lot of people who actually do well and really thrive in having that space and time alone and don't seek that connection."

Solitude is the conceptual antithesis of loneliness which is essential for practitioners to consider when assessing clients' experiences, further illustrating the nuance of loneliness self-disclosure in which being alone does not necessarily equate to feeling lonely. he psychological consequences of loneliness and solitude are distinct. Loneliness is consistently associated with negative emotional experience such depression, anxiety, and cognitive decline (Caple et al., 2023; C. Park et al., 2020), while chosen solitude is linked to emotional regulation, creativity, and autonomy. There is nuance in the impact of loneliness and solitude, Nguyen et al. (2018) demonstrates solitude has a "deactivation effect" reducing excitement, anxiety and anger. When solitude was autonomously chosen, it led to relaxation and reduced stress.

Loneliness Prevalence

From these conceptualisations, practitioners recognise loneliness as fundamentally about meaningful social connection rather than social isolation, distinguishing between social contact and meaningful relational understanding. Practitioners consistently report significant prevalence rates of loneliness concerns in their digital mental health practice. As per Practitioner 4:

> "Probably 80-90% of my clients will feel some degree of loneliness. I think certainly it's more prevalent with the younger clients."

This stark statistic highlights the need for practitioners to be able to identify and develop strategies to reduce the experience of loneliness. Furthermore, the identification of young people presenting with loneliness concerns more frequently than older clients highlights the particular relevance of loneliness recognition for practitioners working with younger demographics. Notably, Practitioner 4 uses the phrase "*some degree of loneliness*", which reveals the nuanced nature of loneliness in which there is a spectrum of loneliness severity. Practitioner 7 gives an overview of loneliness prevalence across the digital mental health platform Kooth:

> "[Loneliness] almost inevitably seems to come up nowadays, and I say even as if that's a surprise [...] The young people, particularly, who appear to be quite well connected socially and that ([Loneliness]) can be a great cause of anxiety for them."

The consistency of high prevalence rates across different digital mental health contexts suggests loneliness represents a fundamental concern requiring practitioner attention.

Practitioner 2 further corroborates this prevalence concern: "*You will find that [Loneliness] will come up with most, if not all of our service users at some point*", as does practitioner 7

> "Just about every client I work with at some level that comes in [expereinces loneliness], whether it's all the time or just some of the time."

The practitioners have identified the significant prevalence of loneliness concerns across a range of therapeutic roles, suggesting that loneliness is not limited to specific client populations or therapeutic contexts.

3.4.2 Theme 2: The Contextual Factors and Causes of Loneliness

Theme 2 discusses the contextual causes across personal, environmental and social experiences that perpetuate the experience of loneliness from the practitioner's perspective. It is notable that identified factors are intrinsically linked to one another in a homogeneous experience rather than defined units of environmental context. From this analysis, two branches of environmental factors appear: the "*Social environment*", of the individual and the "*Physical environment*" in which they live. However, as shown in the following sections, it is often difficult to unravel this combination of lived experience.

Transition, Loss and Loneliness

Life transitions encompass dynamic changes that can break down established support systems and social connections, and are perhaps a quintessential example of the combination of the social and environmental contexts that lead to loneliness. Life transition is a broad term that can encompass a range

of experiences from developmental milestones such as leaving home to attend university, to less predictable life events, including the breakdown of a relationship, bereavement, or job loss, which change an individual's social network.
The impact of people moving for university was a frequent contextual instigator of loneliness (likely because of the age of clients, a majority of the practitioners work with). Practitioner 9 describes: "*When the students first go to university, they feel very, very lonely. It's been a big change for them*". Practitioner 8 elaborates on this experience: "*University students and those that have moved away [...] it comes across as a loss*", in terms of both the environment that they are familiar with and the social connections that were severed. This increase in loneliness as students move to university is prevalent across intervention types and the practitioners identified a number of reasons that lead to this experience, particularly the idea of change and transition from one social group to another. Practitioner 7 contextualises this in terms of social resources: "*I would say almost inevitably, even if someone really wants to be going to uni and they're excited about it, the reality is, so much changes. Similarly, when you leave [University], everything you're sort of like resources change overnight*". This idea of change and experience is also highlighted by Practitioner 6:

> "I've seen a massive influx in the last couple of weeks in terms of universities starting and the number of service users, mainly that are adults, presenting with loneliness around adapting to that change of routine."

Life transition is not limited just to a physical move of location, but can also be linked to the change or breakdown of a romantic or familial relationship. Practitioner 8 describes "*They feel lonely because they've left a relationship or a relationship's broken down [...] They lose themselves because their partner is essentially their whole lif*e".
Practitioner 1 expands on this from their experience as a grief counsellor by identifying how this does not relate only to romantic relationships that have

broken down or finished, but also in a time of death:

> "The [Loneliness] which is caused by the grief and the sense that the person is rendered dysfunctional by the grief."

Describing the isolation during grief, they say "the grief and the type of loss the person is experiencing puts them in a box of isolation", while also linking grief to a social disconnection of friends when experiencing grief from loss: "*there is no one or there are only, a very tiny, tiny number like one or two, max three people with whom they can say they can tell it like it is*". These observations about clients being placed in a "box of isolation" illustrates how external loss can alter entire relational contexts, making previously available forms of emotional expression and social connection inaccessible.

These findings demonstrate that loneliness during life transitions is triggered by a contextual disruption, whether triggered by university relocation, relationship breakdown, or bereavement. Loneliness emerges when established relational patterns are challenged by new environmental demands. The university student's loneliness is brought on by the challenge of navigating new social and environmental contexts where their previously established social experience no longer applies.

This contextual understanding has implications for intervention approaches. Rather than focusing primarily on individual social skill development, these findings suggest that loneliness during transitions may be better addressed through environmental scaffolding, which supports individuals in developing new relational patterns that fit their changed circumstances while maintaining continuity with meaningful aspects of their previous contexts.

Stigma and Social Barriers

Stigma and social barriers emerged as fundamental drivers of loneliness, with practitioners consistently identifying how social exclusion compounds the emotional impact of the concern. Rather than viewing loneliness as a purely emotional state, practitioners identified how loneliness arises through broader patterns of social marginalisation and cultural rejection.

Practitioner 4 identified this distinction between individual experience and societal exclusion, explaining how minority status within a cultural environments creates vulnerability to loneliness:

> "Feeling disconnected from the group because, actually their way of being just doesn't fit with the environment that they're in [...] Often times people kind of get left out."

This conceptualisation moves beyond individual deficits to examine how social structures themselves generate isolation for those who deviate from dominant social norms, whether by choice or not. Practitioner 4 further elaborated on this structural dimension:

> "I think there's loneliness, which is almost the person's internal felt sense of the experience. But also there's exclusion which I think comes from society in general."

This conceptual disconnection is varied and can be unique to the individual, depending on the environment or social norm they are unable to conform to. Cultural and religious differences constituted a significant source of loneliness. Practitioner 3 described how clients from minority backgrounds experienced isolation due to lack of cultural recognition:

> "Feeling isolated because of their faith or their cultural beliefs: 'I'm really lonely because I don't have anyone who's like me."

This form of loneliness presents a sense of cultural misunderstanding. Practitioner 3 further observed how this manifests in social interactions and links to the broader idea of being "*lonely in the crowd*":

> "I think you see a lot of different versions of loneliness show up in identity. And this way of being with people, but feeling quite disconnected or kind of separated from them."

The role of perceived identity and loneliness was evident in practitioners' discussions of sexuality, gender and the impact of heteronormative expectations. Practitioner 4 described how societal norms about gender and sexuality create exclusionary experiences:

> "And I guess you see that in things like heteronormativity and kind of the cisgender expectations that are put on people to [...] look a certain way or present a certain way, whereas actually, who's to say that's the right way?"

This observation highlights how loneliness emerges not from individual ability to form social bonds, but from conforming to social expectations that marginalise those who cannot or will not conform.
Practitioner 9 gave further insight into the impact of not being accepted by family or being able to find a community in which individuals feel included because of their sexual orientation:

> "If either their family aren't accepting [of them being gay] or they're somewhere that where they haven't got good people around them, where they're not accepting [...] can lead to to so many issues and them [...] just spending time on their own and not going anywhere and becoming really lonely."

These observations provide further context for both the emotional experience of loneliness of not being accepted and the specific contextual consequence of being othered due to sexuality or gender. The persistence of such exclusion, despite broader social claims of acceptance and progress, was emphasised by Practitioner 8, who noted the disconnect between societal output and lived reality:

> "I think there's a sense of shame very often even, and I find it quite sad that even today in this time of the world, when we think that it may be more acceptable to have difference of any kind. But

> the reality, the lived reality for a lot of people is not that because they're living in their small personal culture, families who may or may not accept them."

These findings emphasise that loneliness cannot be understood solely as an individual psychological experience, but must be recognised as being shaped by broader social inclusion and exclusion based on identity, culture, and conformity to dominant norms.

The Reduction in Social Resources and Increased Cost of Living

The reduction in social resources provided for both young people and adults is a significant factor in the increase of loneliness, as identified by the practitioners. According to Practitioner 2:

> "I think the general theme for me would be the lack of opportunity [...] to connect with people because when I was a kid, there was youth clubs [...] I went to the library regularly; three of those local libraries now have closed down."

This highlights the effect of a reduction in resources such as social spaces which can make it difficult for young people to connect with others.
The reduction in quality social resources does not only effect young people. Practitioner 5 also identifies the increased cost of living and reduced funding for community services and support:

> "There is also the cost of living [...] the pandemic that forced people, who perhaps maybe have problems in the first place, to go inward as well. In our [area] as well, community services are closing down."

The impacts of a struggling economy can make it challenging for people to go out or engage in social activities as prices continue to increase.

This combined effect compounds as a range of resources become less accessible, creating fewer opportunities for organic social connection across all demographics. When contextualised around deprivation, practitioners identified the stigmatising experience associated with accessing social support, which may limit those who access it. Practitioner 4 highlights this:

> "I think any kind of deprivation often is associated with some degree of loneliness, and I think it thinking about my NHS work actually where people generally I see because they can't afford to have private therapy. And a lot of those clients will be accessing things like food banks or involved in social services."

This summary of broad client concerns identifies how issues are often not faced in isolation but in tandem, those who cannot afford to buy their food and access foodbanks probably are not able to pay for private therapeutic services. Practitioner 4 further identified the stigmatising nature of this experience:

> "Social housing definitely faces a huge amount of challenges that they face day-to-day and I think a lot of that kind of there's the stigma, but also I think there's a lot of embarrassment quite often [...] And I think the embarrassment quite often exacerbates the loneliness. So it's kind of the shame of being on benefits or the shame of accessing a food bank which often is through no fault of their own, it's just circumstances have led them to that point in life."

This reveals another stigmatised experience which exacerbates feelings of shame and loneliness.

The stigma and contextual factors contributing to loneliness, discussed above have profound implications for therapeutic communication. Given the shame associated with acknowledging loneliness directly, practitioners described learning to recognise alternative language patterns through which clients express these concerns.

3.4.3 Theme 3: The Expressions and Associated Language of Loneliness

Theme 3 captures how practitioners recognise loneliness through subtle linguistic cues and expressions rather than direct disclosure (Solano et al., 1982). This theme encompasses practitioners' understanding of the various ways clients communicate loneliness without explicitly saying "*I am lonely*".

Practitioners described the indirect nature of loneliness self-disclosure, identifying typical characteristics of language clients use to describe their emotions. Practitioners also identified differences in the way in which older adults express loneliness compared to young people, and that some clients do not always have the language to express loneliness. Practitioner 3 describes this:

> "They have the feeling but they haven't got the language to go with the feeling, to understand what it is that's going on. And then once they've kind of got some language, it's almost like, well, how do we understand that feeling and what it means to them?"

The limitation of appropriate language particularly affects loneliness disclosure, as clients may feel isolated without being able to name or explain their experience, creating a barrier to self-understanding and support.

When analysing why indirect disclosure is so prevalent, several reasons emerged, particularly the shame and stigma associated with loneliness; leading to embarrassment. Practitioners also explained that clients often give the air of "*its only loneliness*" - (Practitioner 7), and that is not a significant issue that needs addressing. This is combined with the shame of being lonely, of having "*no friends to talk to*" or as Practitioner 5 explains "*a lot of the time I will pick up on real shame, real stigma and this idea of [...] if you're lonely, you're almost like Billy no mates*". While the stigmatised nature of loneliness plays a role in its indirect disclosure, the language used to express loneliness varies based on the contexts driving the loneliness and the age of the client.

Indirect Expressions of Loneliness

A broad range of practitioners identified the frequency of indirect loneliness expressions. Practitioner 9 explains that "*there isn't often that someone will just come out and say I'm lonely*". Or as Practitioner 5 tersely explained:

> "I've not had a client in the last few years that's actually turned around and said '*I'm lonely ever*."

The lack of direct loneliness disclosure may hint at the broader experience of loneliness and show how loneliness is often the result of another contextual experience that results in loneliness, especially not feeling that they have genuine connections with others having no-one to talk to. Practitioner 4 explains that:

> "often times [a client] will use quite broader terms such as "I don't feel like I have anyone to talk to' [...] 'but I don't feel like anyone understands me' or 'I don't feel like that my actual friends."

Practitioners described how proxy terms or "*higher level*" language is used to approach the concern of loneliness. Practitioner 7 gives the following example:

> "[A client says] 'I'm feeling really depressed.' It's like, well, what does depressed mean for you, actually? What does that actually mean, what happens when you're feeling that rather than just accepting that as a term."

Practitioner 2 furthers this by saying "[Depression] has become quite a big umbrella word" which is perhaps taking on a more general meaning of low mood or a melancholic nature. Many of the practitioners identified the use of clinical language to describe feelings of loneliness, which starts through the use of the term "*depressed*", and then the practitioner is able to identify it as stemming from a feeling of loneliness or social isolation rather than the experience of depression.

When higher-level clinical language is used, practitioners often have to unpack these terms to understand what the client is attempting to express. Practitioner 2 explains:

> "[A client] will often use the word depressed, I think sometimes without fully understanding as to where that word's coming from [...] actually it's low mood, it's sadness, it's feelings of isolation or lacking in something in some way of comfort and connection."

Practitioner 7 also identifies this use of clinical language and gives examples of specific words that clients might use

> "Service users might come with kind of overarching themes of what are feel 'depressed', or 'I feel anxious', but when they dig in a little bit [...] other factors or kind of causes or feelings might appear."

While these feelings are no doubt valid, practitioners must differentiate between clients experiencing clinical depression or anxiety and those using familiar mental health terms to express underlying loneliness or social disconnection. There a number of reasons why loneliness may be disclosed through the use of indirect language. Practitioner 7 notes the idea of loneliness often being obfuscated by the client because they feel that it is a "*lesser*" issue:

> "It's partly the shame, but I think some feel [lonely] is almost too simplistic a word like it should be something more complex than this because the feeling of loneliness can be really it can be a really desolate feeling. So there must be something more to it than just loneliness."

This highlights how loneliness occupies a marginal position within contemporary mental health nomenclature as well as remaining stigmatised. While depression and anxiety have become embedded in everyday psychological vocabulary, loneliness lacks equivalent prevalence, and in turn, clients may be using more accessible mental health terminology[1].

The practitioners also identified a nuance in the language used by clients based on their age, in which different similes or metaphors may be used. This use of clinical language can provide further understanding into how loneliness is expressed by different demographics.

Age-related Differences in Expression

Evaluating the differences in loneliness expression can provide a more nuanced understanding of loneliness across age groups and facilitate further examination into the causes of loneliness.

Older people may use direct language about how they are feeling and use what practitioner 7 described as "*traditional*" or "*less technical*" language:

> "*well, yeah, I've been feeling depressed.*" They use traditional language like "*depressed*" or "*flat*", or "*I'm a bit on my own*" whiles lacking the 'complex' language around [Loneliness]".

Practitioner 1 also gave examples used during times of grief such as "*dark*" and "*I don't see the point*", suggesting their loneliness related to absence or meaninglessness.

Younger children employ basic descriptive language but with the consistent avoidance of loneliness terminology present in adults. As Practitioner 2 explains, "*[With] 10 year olds it's like 'feeling low', 'sad', 'alone', it's never really 'lonely'*". The language used by young people can change considerably across the spectrum of ages, as Practitioner 2 continues to break down how language changes: "*Compared with teenaged clients will be a bit more elaborate, 'Withdrawn'*", '*I feel misunderstood*', '*I feel misinterpreted*' or '*I don't feel heard*'. These findings link more broadly to the idea of social acceptance, such as practitioner 6: "*I don't feel like I'm matter*" or "*I don't feel I'm good enough*", or

[1] While potential proxy terms and disclosure strategies have been identified, it is worth noting that loneliness can co-occur with depression and other mental health concerns. This analysis focuses on instances where practitioners identified the depression-related language masked concerns of loneliness.

practitioner 9: "*I can't make any friends. No one seems to like me*". Teenage expression becomes more socially nuanced and metaphorical, which reflects social complexity, with Practitioner 9 also identifying expressions such as "*feeling lost*" or "*helpless*", relating loneliness to social experiences.

Across the age ranges, metaphorical expressions are consistently present: Practitioner 4 identified terms such as "*hollow*", "*empty*" and "*desolate*" as often used by clients to describe feelings of loneliness.

There is also the element of social comparison, which drives loneliness, which can be exacerbated through the medium of social media. Practitioner 4 suggests:

> "For a lot of young people, particularly, [...] in the culture of kind of social media, that there is now everyone kind of looks at the Instagram post and goes how amazing that looks."

This can further entrench the feeling of social rejection and that of being othered.

Highlighting the contextual nature of loneliness, there were differences in the topics and context that appear for young people; younger users unsurprisingly often come with concerns around school, as discussed by practitioner 3:

> "Within the younger users it seems to be a lot more centred around friendships and like school",

and practitioner 2:

> "The majority of your external interaction outside of your family come from those that you interact with in school education"

.

This contextualisation for young people suggests that there are consistent experiences that can serve as potential catalysts for loneliness, as identified in subsection 3.4.2 for adults. School-based loneliness is when young people feel othered. Practitioner 2 expands upon the idea of not feeling a meaningful connection and how this can affect young people:

> "If you don't feel like you're connecting with those around you, it could be that you've got micro interests, your interests that are in this very small bubble others don't actually share."

This idea was identified in subsection 3.4.1 where clients struggle to find meaningful connections with others. There are also different types of contextual loneliness that can occur from those who face rejection from their peers, as opposed to the loneliness felt by a bereaved individual.
These age-related differences in loneliness expression reflect how individuals develop a self-descriptive vocabulary as they navigate increasingly complex social environments, yet consistently avoid direct loneliness terminology. While children use basic descriptive language and teenagers employ more socially aware terminology, both groups avoid explicit self-disclosure. Similarly, older adults may use more traditional language but still rely on proxy terms like 'depressed' or 'flat.' Regardless of age-related expression, this avoidance reinforces loneliness as a stigmatised experience that requires careful therapeutic consideration across all client demographics.

3.4.4 Theme 4: The Co-occurrence of Loneliness and Mental Health Concerns

Theme 4 evaluates the co-occurrence of mental health concerns and loneliness. While clinical language around mental health concerns may be used by some clients (identified in subsection 3.4.3) as a proxy for loneliness concerns, it is also valuable to evaluate practitioners' understanding of the specific relationship between mental health concerns and loneliness. Particularly, the impact of severe mental health conditions or presenting issues, the causal relationship identified by practitioners, and broader social consequences for those experiencing mental health episodes.

Pathways to Severe Mental Health Issues

Feelings of invalidation were identified by practitioners as a driver towards severe mental health concerns, which result in and are a consequence of loneliness. Practitioner 4 gives an example of the invalidation that arises from exhibiting traits of more severe mental health disorders, specifically discussing clients with Emotionally Unstable Personality Disorder (EUPD) and Borderline Personality Disorder (BPD):

> "There's a lot of invalidation about their experience. They're 'too upset' [...] including the systems that in theory are there to support them, quite often, do invalidate, to kind of add to that disconnect."

This shows a link between stigmatised experiences that lead to feeling invalidated, and experiences of social disconnection and loneliness. Practitioner 9 elaborates on this link:

> "All mental health disorders really can lead to [Loneliness] and the people that are, [...] very traumatised as well, people that have had really invalidating, [...] upbringings where the parents haven't been good."

This further elucidates the connection between poor social support from those with whom individuals are close and stigma, which are described as being experienced in tandem.

Feelings of loneliness can intensify presenting mental health concerns, with the relationship between loneliness and risk in those engaging in digital mental health interventions, as described by practioner 9:

> "The impact of loneliness on people who are already in the severe category [of mental health concern] is so significant [...] the potential impact of their becoming lonely and the risk to life are so significant."

This is a stark insight into the consequences of loneliness combined with severe mental health issues; this is particularly pertinent as Practitioner 3 describes a potential progression from social issues such as friendship problems or low self-esteem to "*higher presenting risks" with "Friendship issues or some self esteem issues lead[ing] to higher presenting risk*". This progression suggests escalation toward self-harm or suicide risk. This establishes a need for intervention when the presenting risk is high, as Practitioner 3 again identifies

> "it can be quite challenging when the young person is quite focused, almost quite fixated on like these feelings almost and their perception of the situation."

This highlights the pathway of higher risk presenting issues resulting in more severe consequences while also causing experiences of loneliness.

Loneliness as a Consequence of Specific Mental Health Concerns

While depression and anxiety have become less stigmatised in modern daily living, the impact of less common concerns can lead to an increased experience of loneliness due to their intense impact on the individual's behaviour, in part due to these issues being still significantly stigmatised. Practitioner 9 gives specific examples for psychosis and personality disorders:

> "Major mental health illnesses like psychosis, you know, and personality disorders are still a massive stigma where people, you know, just don't want people to know but because their symptoms are so intense because they've [people with personality disorders] had so much abuse and trauma in the past. And the only way they know how to get a connection is by you know, kind of very extreme behaviours, which can be really risky."

This quote identifies how major mental health concerns, which have intense symptoms and can be a result of trauma, result in the individual resorting to risky health behaviours to facilitate a connection.

This isolating behaviour can stem from two routes: first, there is the emotional impact of stigma and shame. As practitioner 9 explains:

> "The shame and everything that comes with [being manic], often they're more prone to isolating themselves anyway and becoming lonely because they're depressed."

Here, self-isolation arises from feelings of embarrassment or fear of judgment, leading individuals to withdraw from social contact. Secondly, isolation can result directly from the symptoms of the mental health condition itself. In the case of schizophrenia, practitioner 9 describes:

> "with schizophrenia that are so paranoid because of their illness [...] some of them will only accept that absolute bare minimum [...] some of them, they won't even dare put the TV on because they think people are communicating with them through the TV. So you have people like that who are just in their homes just on their own."

In this second pathway, withdrawal is driven by intense paranoia and delusional thinking rather than stigma or shame, which limit contact with the outside world.

When the result of a severe mental health issue is hospitalisation, the individual's propensity towards self-isolation and loneliness can increase because of the physical and social separation imposed on those who have been hospitalised, further increasing feelings of loneliness and isolation. Practitioners also mentioned the impact of specific mental health concerns and loneliness as a co-occurring feedback loop. This link between serious mental health conditions or "episodes" which require hospitalisation results in stigma and physical isolation. This consequence was identified by Practitioner 6

> "For young people, I find that when they struggle with their mental health, they do tend to lose a lot of friendships sadly and especially

> if they've for example self harmed or attempt to take their own life and they need a hospital admission, a lot of friends then drop them."

Practitioner 6 gives a quote from a service user who was hospitalised

> "The image that they describe to me is when I look out of the window of the hospital, all I see is my reflection staring back at me. There's no one like behind us to show that I'm cared for or I'm looked after".

3.5 Discussion

Across all four themes, practitioners described loneliness as a complex experience shaped by a combination of internal feelings, relational contexts, and broader social structures. The findings show that loneliness is rarely disclosed directly, often masked by proxy language or overshadowed by co-occurring mental health concerns. Furthermore, loneliness is caused by a range of factors, from life transitions and structural stigma to the symptoms of severe psychiatric conditions. This complexity means that loneliness cannot be reduced to the absence of social contact, but must be understood in terms of the quality, meaning, and accessibility of relationships within each client's lived environment. These observations highlight the importance of practitioner skill in recognising subtle expressions of loneliness and addressing both its psychological and social structural drivers. The discussion that follows situates these findings within the wider literature, examining how they align with, challenge, and extend existing understandings of loneliness in digital mental health contexts.

This chapter has further presented the significance of stigma as a facet of the loneliness experience. Stigma operates at two levels within the experience of loneliness: 1. stigma functions as a contextual instigator which increases the propensity for loneliness (through social exclusion and identity-related isolation); and 2. the intrinsic stigma and shame associated with being lonely, which persists as a barrier to explicit self-disclosure in therapeutic environments. This dual-role of perspective of stigma expands upon previous research identifying the interaction between stigma and loneliness, particularly as practitioners were able to identify loneliness concerns through this relationship between stigma and loneliness, suggesting that this interaction can serve as a proxy indicator for identifying potential loneliness triggers in clinical practice. The range of practitioner insights about disconnection and a lack of quality social connections also aligned with established literature (Fardghassemi & Joffe, 2022; K. E. Martin et al., 2014) and the items in prevailing loneliness measures (particularly the UCLA and DJG Loneliness scales). This finding resonates with specific concepts from the existing scales, and their core conceptualisations of loneliness, in which limited meaningful connections are present for the individual experiencing loneliness (as summarised in Table 3.4): Item 6 and 9 from the UCLA loneliness scale: "I have a lot in common with the people around me" and "My interests and ideas are not shared by those around me" mirror the observations from practitioners that people may feel a lack of connection with others due to surface level interests. This extends to indirect expression of loneliness, for example "*I don't feel like they are my actual friends*" mirrors item 12 in the UCLA loneliness scale "*My social relationships are superficial*".

The DJG scale items further reflect practitioner observations about client language patterns. The item "*I experience a general sense of emptiness*" aligns with practitioners' reports that clients frequently use metaphorical expressions such as "*hollow*", "*empty*", and "*desolate*" to describe their loneliness without using direct terminology. Similarly, the DJG item "*I miss having people around me*" corresponds to the indirect expressions practitioners identified, such as "*I don't feel like I have anyone to talk to*". The DJG item "*I often feel rejected*" particularly aligns with practitioners' observations about clients experiencing stigma-based social exclusion, whether due to cultural identity, sexuality, or other marginalising factors. It is important to note that some of the phrases used to describe feelings of loneliness are similar to items included in the UCLA and DJG scales. While these keywords have been identified by practitioners, these scales were developed in the 1960s and 1970s, suggesting that the ways individuals describe feelings of loneliness has not changed over time.

Table 3.4: Loneliness Self-Disclosure Terms Identified in Loneliness Measurement Items

Keyword	**Measure / Item No.**	**Item Text**
Companion / Companionship	UCLA (Item 1)	I lack companionship.
Left Out	UCLA (Item 10)	I feel left out.
Nobody	UCLA (Item 13)	No one really knows me well.
Isolated	UCLA (Item 14)	I feel isolated from others.
Withdrawn	UCLA (Item 17)	I am unhappy being so withdrawn.
No one to turn to	UCLA (Item 20)	There are people I can turn to.
Miss friends	DJG (Item 2, Item 9)	(2) I miss having a really close friend. (9) I miss having people around me.
Emptiness	DJG (Item 3)	I experience a general sense of emptiness.
Friends	DJG (Item 4, Item 11)	(4) There are plenty of people I can rely on when I have problems. (11) I can call on my friends whenever I need them.
Trust	DJG (Item 7)	There are many people I can trust completely.
Rejected	DJG (Item 10)	I often feel rejected.

This highlights that loneliness conceptualisation by practitioners in a digital mental health context aligns with established theoretical frameworks and measurement approaches. Specifically, practitioner perspectives connect directly with the definition provided by Hawkley and Cacioppo (2010) as the "*subjective perception of a discrepancy between the desired and true social re-*

lationships in terms of companionship, connectivity, or intimacy". Together, these parallels across both measurement tools underscore that practitioner perspectives reflect the same relational and emotional dimensions captured in validated loneliness scales, while revealing how these experiences are expressed indirectly in therapeutic contexts. This may warrant further investigation, as it is unclear whether the coalesced conceptualisation is due to the practitioners having been trained on the established scales and concepts, which have shaped their perception, or if their understanding of loneliness is based purely on their experience of interacting with and supporting lonely service users.

This work also builds upon previous research on the language of loneliness, demonstrating that elicitations of loneliness by clients in traditional therapeutic environments align with those in online and digital interventions (Heu et al., 2021; Verity et al., 2024). Service users' elicitation of loneliness provided practitioners with a number of insights, particularly the language used by clients when expressing loneliness and the typically indirect approach taken.

These findings extend the findings provided by Verity et al. (2021) in which young people described a discrete set of emotions to characterise the experience of loneliness, including "*sadness*", "*anger*", "*emptiness*", "*feeling unloved*", and "*hopeless*". Furthermore, several practitioners noted that clients would disclose feeling disconnected or express hopelessness about their social situation without directly acknowledging the feeling of loneliness. These feelings, which relate to the experience of loneliness, were identified as indirect expression, particularly practitioners reporting clients describing themselves as "*depressed*" rather than lonely, which aligns with the work by Cacioppo et al. (2010) in which there is some overlap in the experience of both depression and loneliness. However, this research identifies that this disclosure of depression could be due to the client's clinical vocabulary rather than their true experience. More specifically, depression is used as a description of how people feel, which may be true for clients, which is distinctly different from loneliness as a specific feeling related to the lack of social connection as established by

(Cacioppo et al., 2010; Weiss, 1975).

This analysis provides novel perspectives into the specific ways in which loneliness is elicited by different age groups, identifying a previously undocumented developmental progression in loneliness language. The language used by older people is often more direct and "*traditional*" compared to the clinical terminology that has become embedded in young people's emotional vocabulary, suggesting that mental health literacy may incongruously create new barriers to authentic emotional expression.

The prevalence findings reveal how loneliness impacts individuals' approaches to therapeutic disclosure in digital intervention environments. While practitioners report that "*80-90% of their clients experience loneliness concerns*", clients seldom express this directly. These findings extend existing loneliness measurement theory by putting value in loneliness measurement tools that do not use direct loneliness questions, such as "*how often do you feel lonely?*" Rather, these findings validate the effectiveness of indirect assessment approaches while providing insight into their efficacy, due to interpersonal stigma preventing direct therapeutic disclosure.

The contextual triggers of loneliness that were identified by practitioners were numerous, particularly affecting those who have minority status within a dominant culture and face challenges in conforming to social norms because of their individual cultural background. This type of stigma extends to specific faith and cultural beliefs, which can lead individuals to feel disconnected from the broader cultural norms that surround them. Other specific examples include LGBTQI+ or neurodiverse populations (Barreto et al., 2022; Dahlberg, 2007) whose experiences are less understood or who are actively othered by their community. While cultural difference where identified by practitioners this may be extend to the experience of those who immigrate.

The practitioners identified a number of contextual factors that co-occurred with loneliness across the four themes. The significant impact of life transitions identified by practitioners aligns with Lim's (2020) assessment of loneliness triggers, where life transitions precede and instigate loneliness. Practitioners identified similar triggers such as moving away from home (specifically for university) (Fardghassemi & Joffe, 2022), divorce (the breakdown of a relationship)(Schobin, 2022), or death of a spouse (and the associated grief and loss)(Fardghassemi & Joffe, 2022). Practitioners also identified the impact of being

The practitioners also identified reductions in social spaces and government resources combined with an increased cost of living as contributing contextually to loneliness through both a limitation in social activities due to cost, and in the stigma of having to engage in social support, such as food banks or engaging in benefits programmes; this aligns with and expands on insight by Cheetham et al. (2019). These factors build upon previous research identifying the contextual nature of loneliness while also providing evidence that these elements are also consistent in online environments.

A notable driver was the relationship between severe mental health and psychiatric disorders with loneliness as identified by (Mushtaq, 2014) and (Gasull-Molinera et al., 2024). This loneliness presents as a sequela of severe mental health conditions, such as the isolating effects of being in treatment and being away from family, friends and an established support network, the social stigma of having a major mental health illness and the consequence of self-isolation that is inherent with specific mental health concerns such as being manic or depressed.

While the contextual factors and drivers remain consistent amongst practitioners in traditional face-to-face interventions and those who practice on digital platforms and online, novel insight has been gleaned into the way in which clients, specifically younger clients, elicit concerns of loneliness. Further, it is also clear that, regardless of the environment, loneliness is still elicited indirectly through a range of metaphors and similes in order to minimise the perceived stigma of loneliness.

3.6 Limitations and Future Work

Several limitations should be acknowledged. Recruitment challenges within the specialised population of digital mental health practitioners limited the final sample size to nine participants. The sample was overwhelmingly female (7/8 participants) and entirely White British (where reported), potentially limiting the generalisability of findings across diverse practitioner and client populations. However, the achieved sample demonstrated strong conceptual diversity across practitioner roles (grief counselling, DBT therapy, LGBTQ+ specialisation) and platform types (Kooth, TogertherAll, private practice), supporting the credibility of identified themes.

Following recommendations for pragmatic saturation assessment (Hennink & Kaiser, 2022), saturation was evaluated based on sufficiency of data to address research objectives. The central patterns of loneliness expression, contextual causes, and practitioner recognition had reached sufficient depth for meaningful analysis, though additional participants might have provided further nuance.

While this study identified how loneliness is expressed indirectly in therapeutic contexts, questions remain about how digital mental health interventions can effectively address loneliness given these indirect disclosure patterns. The practitioners' perspectives suggest that understanding service users' underlying wants and needs, rather than relying on direct loneliness disclosure, may be crucial for developing effective loneliness interventions. This provides the foundation for examining how frequently loneliness-related concerns appear among the broader wants and needs expressed by digital mental health service users.

It should also be noted that these insights were gathered from practitioners discussing digital therapeutic contexts and future work should be undertaken to evaluate if the identified concerns are true for in person therapeutic interventions.

Whilst this thesis does not explicitly examine immigration status as a predictor variable, it is important to acknowledge that international students and immigrant populations may face compounded loneliness risk factors. Similarly, the immigration status of an individual (such as achieving "home status") may intersect with loneliness in ways that warrant consideration. These represent important areas for future research to explore how structural and demographic factors interact with the mechanisms of loneliness examined here. Furthermore, there was limited insight generated into the experience of those in which English is a second, third or fourth language, how this may impact their ability to self-disclose loneliness in a way that practitioners can interpret; and how this might expressed based on the individuals culture.

3.7 Concluding Remarks

Practitioners identified multiple stigmatising experiences as contextual drivers of loneliness, highlighting how loneliness emerges not only from individual factors but from broader patterns of social exclusion and marginalisation. For therapeutic practice, these insights suggest that practitioners can use awareness of stigmatising experiences as potential indicators when assessing loneliness risk. The presence of these contextual patterns was consistent across both digital and traditional therapeutic environments previously identified in the literature, providing a foundation for developing more targeted interventions that address both the emotional experience of loneliness and its underlying social drivers across therapeutic environments.

Chapter 4

Digital Mental Health Outcome Measures - The Single Session Wants and Needs Outcome Measure

Abstract

Background

Current outcome measures in digital mental health interventions lack granularity, especially for single-session interventions. This study aims to address this by utilising Natural Language Processing (NLP) methods to create a clear and relevant outcome measure. This chapter describes the development of the Adult Session Wants and Needs Outcome Measure (Adult SWAN-OM), a novel outcome measure for the Kooth digital mental healthcare platform (DMHP) to understand service user (SU) needs engaging in single-session therapy (SST). This study enables a border evaluation of DMHP SU needs and identifies if loneliness is explicitly expressed as a therapeutic concern within digital mental health interventions.

Methods

The research employs a multi-phased approach combining NLP methods with the typical stages of outcome measures development: 1. assumption definition and validation with SUs and clinicians; 2. transcript theme extraction using the RoBERTa large language model (LLM) in conjunction with topic modelling to extract themes from 254 single-session transcripts from 192 SUs; 3. clinical item refinement focus group; 4. content validity with clinicians and SUs to improve the relevance and clarity of the items; and 5. outcome measure finalisation in a workshop held with clinicians to consolidate the final wording.

Results

96 potential wants and needs were generated through workshops with practitioners and distilled into 12 measure items. The outcome measure was shown to be relevant and clear to both SUs and clinicians when used in the context of SST. While SUs did not directly appear as an item in the Adult SWAN-OM outcome measure, items which could signal loneliness were identified, such as "Be heard and understood", "Building my support system" and "Help with grieving a loss" which related to the themes identified by practitioners in Study 1 (chapter 3).

Conclusion

This study highlights the potential of combining NLP approaches with co-creation methods in single-session outcome measure development. This study argues that the incorporation of clinical expertise and SU experience ensures the clarity and applicability of such measures and that this approach to capturing single-session wants and needs promises novel insights for supporting digital mental health interventions. This chapter also identifies a number of wants and needs which align with the potential indirect disclosures of loneliness.

Practice and Policy Implications

Implication For Practice 1

This work will enable practitioners to quickly understand the clear and relevant wants or needs of a service user participating in single-session therapy on digital mental health platforms.

Implication For Practice 2

The work also addresses a key challenge in single-session therapy delivery, in which there are no applicable, accessible outcome measures that are actionable in a single-session therapy delivery, and this outcome measure solves the challenge by presenting 12 potential outcomes that a service user could want to achieve in a single session.

Implication For Practice 3

The work identifies "Feeling heard or understood", "Building my support system", "Help with grieving a loss" are outcome items which may represent an issue for a SU in which they may be experience feelings of loneliness and therefore practitioners can align the single session to present strategies for reducing loneliness.

Implication For Practice 4

This study shows the process of developing a single-session outcome measure using contemporary NLP techniques and how to combine these methods with well-established qualitative methods such as workshops. Providing insight into the application of large language models in evaluating transcripts in a single-session therapeutic context.

4.1 Introduction

The advent of digital mental health platforms such as Kooth, in which data about service users (SUs) is collected at scale presents researchers with a methodological opportunity to understand why SUs are engaging in therapeutic interventions more broadly *and* if direct or indirect concerns of loneliness are present.

Qwell (a sub-platform of Kooth) is a DMHP commissioned by the British National Health Service (NHS), local authorities, charities, and businesses. Through this platform, a SU can access an online peer community and a team of emotional wellbeing practitioners. Qwell is anonymous at the point of use and free to access. Due to the wide-reaching and person-centred service model, there is a varied range of SU needs. This project builds upon the Kooth Session Wants and Needs Outcome Measure (SWAN-OM), designed by (De Ossorno Garcia et al., 2021), to develop a novel single-session outcome measure that aids in understanding the idiographic (personalised) wants and needs of service users by extracting recurring themes from single sessions on the Kooth and Qwell platforms.

Outcome measures can be used within DMHPs to provide insight into the wants and needs of SUs. Single sessions offer SUs the opportunity to talk about problems, receive helpful advice, be referred to other resources and have direct access to intervention (Hymmen et al., 2013). However, (De Ossorno Garcia et al., 2021) suggest there is not a sufficient measurement for this type of intervention which translates patient needs into achievable outcomes. Two types of sessions are evaluated in this work: 'single sessions' and 'one-at-a-time sessions' of between 2 and 5 sessions. This research shows how contemporary machine learning methods can be applied to the ubiquitous and often unused text data generated within DMHPs, and its uses in the development of an outcome measure through the analysis of transcript data.

4.1.1 Outcome Measures: Development and Application

For an outcome measure to be useful in a clinical environment, clients must be able to assign meaning to items in the measure and identify goals they find useful (Kwan & Rickwood, 2015). The process for developing outcome measures is typically done via focus groups and expert panels with a combination of SUs, clinical experts or practitioners (Blais et al., 1999; Rose et al., 2011); this study builds upon this existing approach of developing outcome measures by combining focus groups and expert panel insight with the evaluation of transcripts from therapeutic sessions between practitioners and clients.

Outcome measures often follow two approaches: nomothetic approaches consist of validated outcome items based on population norms, and idiographic approaches are based on personalised items for individual patients rather than broader populations (Ashworth et al., 2019). Outcome measures can be used to understand specific problems or concerns, such as depression (Patient Health Questionnaire-9, PHQ-9) (Kroenke et al., 2001) or anxiety (Generalised Anxiety Disorder-7, GAD-7) (Spitzer et al., 2006). Nomothetic measures are used for determining more general therapeutic outcomes including the Young Person's CORE (YP-CORE) (Twigg et al., 2009), the Clinical Outcomes in Routine Evaluation Outcome Measure (CORE-OM) (Evans et al., 2002), and The Kessler Psychological Distress Scale (K-10) (Kessler et al., 2003) .

SST is a therapy that lasts for one session; there are several reasons why a client may partake in just one therapy session. Dryden (2020b) defines two primary types of SST, 'single-session therapy by default' is where a client books a series of sessions but only attends the first session and does not return to complete the subsequent sessions. In contrast, 'single-session therapy by design' is a when a client arranges and completes a single therapy session with a therapist. The delivery of SSTs differs from other long-form interventions as the help is provided during one session rather than multiple sessions over a period of time. However, it should be noted that having a single session does not rule out the option of future sessions (Dryden, 2020a). 'One-at-a-time' (OAAT) interventions can also be part of the SST approach Hoyt et al. (2018); although a single session is not initially part of a wider treatment plan, SUs may take part in several OAAT sessions depending on the therapeutic needs of the client. (Young & Dryden, 2019) suggest the increase in the uptake of SSTs/OAATs can be seen as a response to the increasing need for accessible and responsive mental health service delivery.

4.1.2 Developing Outcome Measures for Digital Environments

Mindel et al. (2021) evaluated the suitability of three measures to understand the needs of SUs in the context of the DMHP Kooth: The Short Warwick-Edinburgh Mental Wellbeing Scale (SWEMWBS), The Strengths and Difficulties Questionnaire (SDQ) and YP-CORE (Clarke et al., 2011; Goodman, 1997; Twigg et al., 2009). Based on the judgement of clinical practitioners within Kooth, all three measures demonstrated validity when used as indicators of user-rated needs upon entry to the platform; YP-CORE was the more appropriate measure in this context as YP-CORE can be used to measure both user needs and user outcomes. Although these measures can be used to understand SUs' needs, (Hymmen et al., 2013; Mindel et al., 2021) suggest that a better understanding of SUs' needs and greater impact of outcomes would be achieved by combining standardised measures with a more personalised assessment of the individual.

An initial attempt at a data-informed outcome measure is the SWAN-OM (De Ossorno Garcia et al., 2021); the SWAN-OM consists of a total of 21 outcome items split across 6 themes that aim to capture in-session goals and focus on the elements critical to the success of single-session and brief interventions. When administered across a 6-month period to 1,401 SUs, the most frequently selected responses were "Feel better" and "Find ways I can help myself", while less commonly selected responses included “Feel safe in my relationships” and “Learn the steps to achieve something I want” (De Ossorno Garcia et al., 2022). Although the SWAN-OM provided insight into the development of a more robust outcome measure tailored to the digital mental health space, there were limitations to this work, primarily the small sample of transcripts analysed. This research builds upon previous work developing outcome measures (De Ossorno Garcia et al., 2021; Denner & Reeves, 1997; Honary et al., 2018) by evaluating 38420 transcript messages across 254 conversations using contemporary NLP methods to extract a more representative configuration of SU wants and needs.

4.1.3 Natural Language Processing in Digital Mental Health

NLP is a collection of computational techniques for learning, understanding, and producing human language content (Hirschberg & Manning, 2015). Topic modelling is a NLP technique that can be used to represent large amounts of data in low dimensions and present hidden concepts, latent variables and prominent features of a corpus (Kherwa & Bansal, 2018). Dynamic topic models can provide a more nuanced understanding of the topics in a corpus and how the topics change over time (Blei & Lafferty, 2006). Transformer models have enabled considerable advancements in the field of NLP, with a widely cited transformer architecture being the Bidirectional Encoder Representations from Transformers (BERT) (Devlin et al., 2019). BERT and other LLMs can be modified to focus on a specific discipline by fine-tuning them on a corpus from that discipline, for example, Med-BERT (Rasmy et al., 2021)and BioBERT (Lee et al., 2020). These methods have wide ranging applications within mental health fields such as detecting specific mental health concerns or improving practitioner workflows.

In the context of mental health informatics, NLP has been employed for a wide range of applications, from understanding general wellbeing, for example, predicting satisfaction with life by applying topic modelling techniques to Facebook message transcripts (Schwartz et al., 2016) or estimating the wellbeing of populations using 1.53 million geo-tagged tweets (Jaidka et al., 2020). Examples of NLP use cases for specific mental health concerns include recognising schizophrenia in corpora, detecting suicide ideation from counselling transcripts, and analysing social media data to detect depressive symptoms (Althoff et al., 2016b; Coppersmith et al., 2018; Oseguera et al., 2017; Strous et al., 2009). Cook et al. (2016) showed that NLP models can generate relatively accurate predictions in identifying individuals at risk of psychological distress or suicide by using answers from a simple questionnaire about the patient's mood. These approaches can assist clinicians by quickly extracting and synthesising valuable information from text written by SUs.

Despite the versatile applications of NLP in mental health support, there are often limitations to the studies that prevent actionable insight for service delivery based on the outputs of said NLP techniques. This is primarily due to limited access to real-world data (Liu et al., 2021). Publicly available data, often from social media platforms such as Facebook, X (formerly Twitter) or Reddit, are often used in place of sensitive and difficult to acquire therapeutic transcript data (Zeberga et al., 2022). This leads to insights that are not completely transferable to therapeutic practice owing to the different contexts of a social media platform compared to a DMHP. Although these research insights are useful, the way in which users engage with a public-facing social media platform is significantly different from the approach a SU would take in engaging with a digital mental health intervention. Therefore, the textual insights gleaned from an NLP model would also be different. This work addresses this contextual disparity by using real-world transcript data from DMHPs and applies contemporary NLP methods to understand the needs of SUs in the context of SSTs.

4.1.4 Study Rationale, Research Aims and Objectives

The primary rationale of this study is to explore how NLP techniques can be harnessed to aid the understanding of the wants and needs of SUs concerning single-session therapies on DMHPs.

This research aims to answer the question of how NLP methods can be applied to a corpus of DMHP transcripts to generate a clear and relevant outcome measure for adult users participating in SSTs on DMHPs with the objective of defining and validating a novel single-session outcome measure that captures SUs' wants and needs. This aim also enables an understanding of indirect loneliness concerns and to be able to find wants and needs that could be a trigger of loneliness.

The research aim and objective is to be achieved by answering the question: How are SU needs expressed in digital mental health interventions, and what methodological approaches can best capture them?

This study aims to make the following contributions:

1. A novel outcome measure for adults participating in SSTs.
2. Utilising NLP methods in the development of a single-session outcome measure for a DMHP.
3. Providing insight into the development of an outcome measure through the analysis of conversation-level transcripts.
4. Incorporating the perspective of individuals with experience of engaging with SSTs in the design of a single-session outcome measure.
5. Identifying and extrapolate items that could suggest indirect loneliness disclosure

4.2 Methods

The development of this outcome measure followed a multi-phased design process, informed by outcome measure development literature, particularly on participatory research, involving focus groups comprised of clinicians and individuals with lived experience in engaging with DMHPs. The outputs from the NLP analysis of conversation transcripts between SUs and practitioners underwent evaluation by both clinicians and individuals engaging with DMHPs. This evaluation guided the creation of a set of outcome items, which were further refined through content validity sessions involving Qwell clinicians, practitioners, and experts in SSTs.

The data were provided and anonymised by Qwell. This secondary data was processed by Qwell to ensure the transcripts did not contain any personally identifiable information, and this study received a favourable ethical opinion from the University of Nottingham's Business School ethics board. The transcripts analysed were from Qwell SUs that had previously provided research consent regarding the evaluation of their therapeutic transcripts. Informed consent was also gathered from participants of the workshops undertaken throughout this study.

4.2.1 Dataset and Demographics

The data used in this study consisted of transcripts between practitioners and SU's (n=874) at conversation level (n=2323). A filter was applied to the dataset to ensure that various inclusion criteria were met. The inclusion criteria are as follows: the SU must have previously given consent for their data to be included in Qwell research studies. Each session must be longer than 8 minutes, a timeframe defined by Qwell to ensure the SU actively participated in the session. The session should have no 'named worker' associated with it and must be a drop-in single session. Finally, the transcript must have an associated End of Service Questionnaire (ESQ). The process for this filtering criteria can be seen in Figure 1.

Individuals in the final selected cohort (n=192) are not significantly different from the wider Qwell SU population during the study period (n=874) in terms

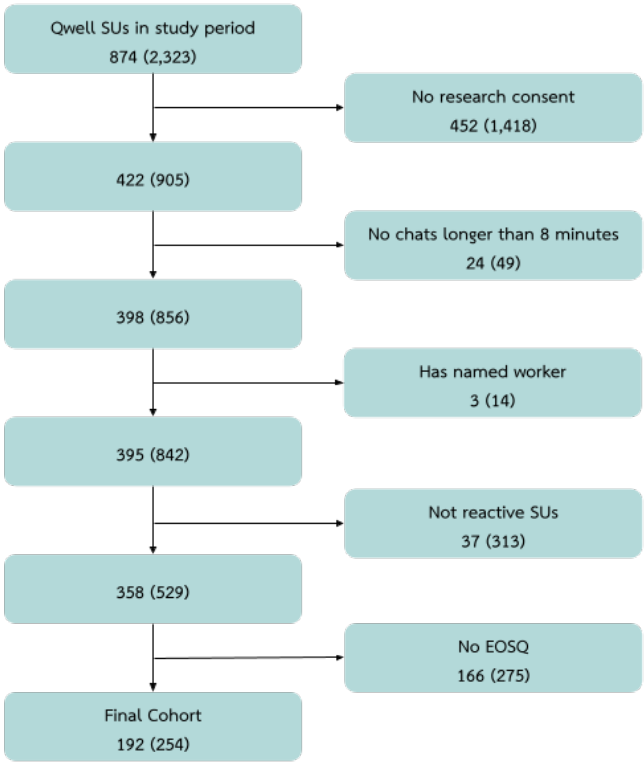

Figure 4.1: *Cohort Flow Diagram (Numbers in brackets represent the count of unique conversations between an SU and a worker)*

of age, gender or ethnicity, suggesting that the cohort is representative of the wider target Qwell SU population. Each conversation was assigned a label based on the SU's rating of the session via an ESQ presented to the SUs at the conclusion of the session.

Phase 1: Assumption Definition and Validation Workshop

An initial workshop included people with experience engaging with DMHPs and Qwell clinicians to walk through the assumptions that were to be made when collecting and evaluating the transcript data used in this study. Assumption 1: The ESQ is an accurate representation of the extent to which SU's wants and needs are met during a single session. Assumption 2: SUs need to identify their wants and needs in the session for them to be met. These assumptions facilitated the identification of transcripts and conversational components that align with wants and needs being met within a single session. The text data from successful or 'useful' single sessions (determined by assumption 1) could be used to find topics to determine the wants and needs of SUs when entering single sessions. This workshop session enabled the researchers to gain insight into the thoughts of people with experience of engaging with DMHPs and contextualise the planned methodological approach with the participation of SUs and Qwell clinicians.

Phase 2: Transcript Theme Extraction Process

When SUs complete a text-based therapeutic session with a Qwell practitioner, they are presented with an optional ESQ, a 4-item questionnaire that the SUs fill out to reflect on the quality of the session. The ESQ contained four items, “I felt heard, understood and respected”, “What we talked about was important to me”, “The person helping me was a good fit for me” and “Overall, the session was right for me”; the items were rated on a scale of -1 (Not at all), 0 (A little), +1 (A lot), for a total score for the ESQ of -4 to +4 for each user. The outcome score was used as the dependent variable in the training of a supervised learning algorithm to extract the textual features that contribute towards positive and negative single-session outcomes.

A RoBERTA regression classifier was trained on transcript data from 2323 single sessions to extract textual elements that contributed to a successful session (higher ESQ scores). To understand what elements of each message were most impactful in the outcome of a session, the transformers-interpret model (Janizek et al., 2021) was used to extract word attributions from positively classified messages. Positive word attributions were then passed through a contextualised topic model (CTM) (Bianchi et al., 2021) to extract and group positive word attributions into 10 topics; this process flow can be seen in Figure 2. Through a qualitative evaluation with a data scientist within Kooth and clinicians the results of the topic model was deemed the most useful in terms of the insight that could be gleaned from the topic model word clouds.

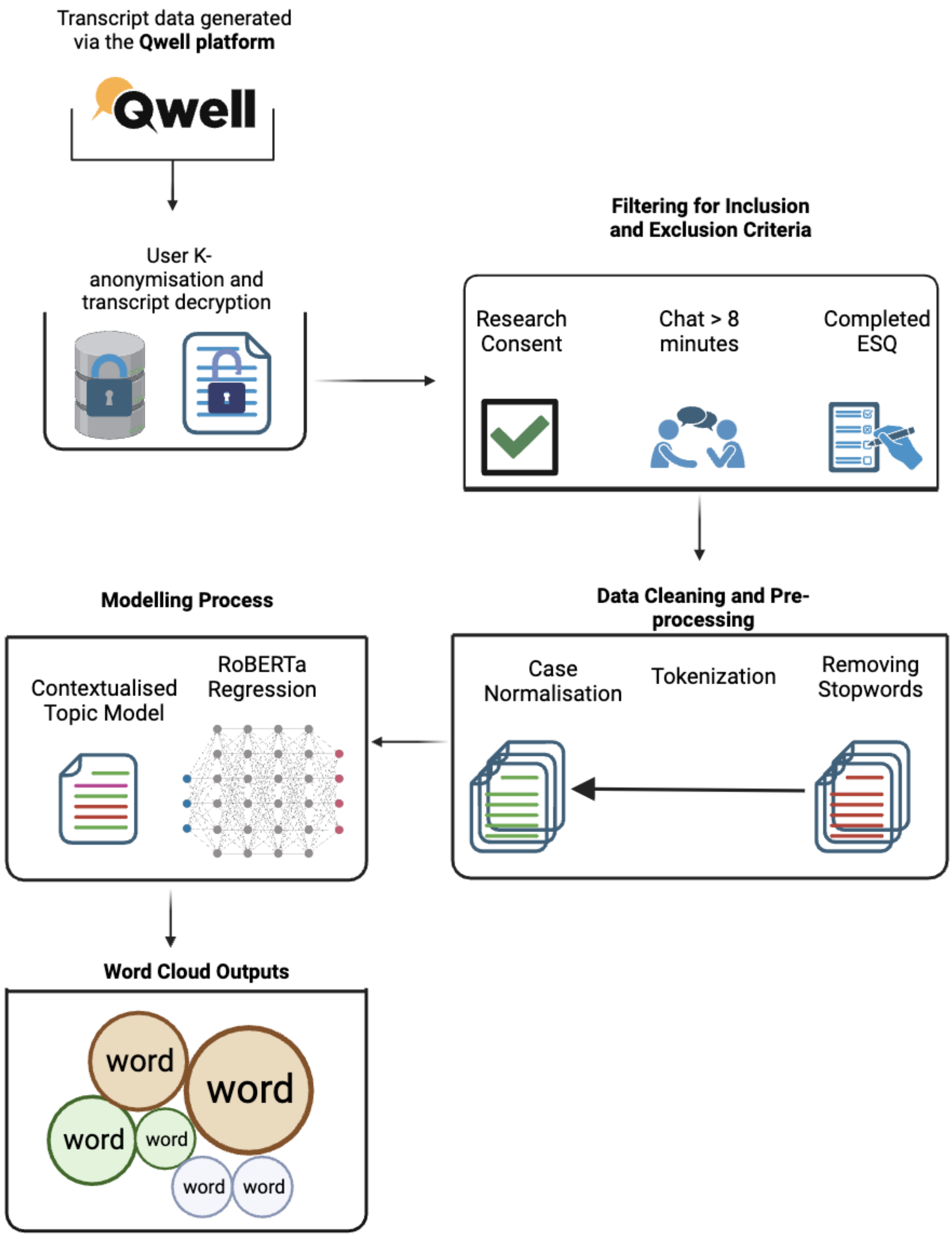

Figure 4.2: *Topic Modelling Process Flow Diagram*

Phase 3: Clinical Item Refinement

The topics generated in Phase 1 were presented to a focus group of expert clinicians within Qwell to establish an initial set of outcome measure items; these items were refined into a smaller subset of items that encapsulate the spectrum of potential SUs wants and needs. The initial measure items were structured into a content validity survey, which involved presenting the items to SUs and experts to assess the relevance and clarity of the items in the context of SSTs. The experts were then able to judge the quality of the outcome measure while also providing insight into the clarity and relevance of the items.

Phase 4: User and Clinical Content Validity Analysis

Content validity is the degree to which an instrument has an appropriate sample of items for the construct being measured. The Content Validity Index (CVI) is a widely used index for the evaluation of outcome measures; a panel of Qwell clinicians and Qwell SUs were asked to rate each scale item in terms of its relevance and clarity as a want or need within the Qwell single session. SUs were consulted first, being presented with the initial items generated in phase 2; they rated the items for relevance and clarity following the Item-level CVI (I-CVI) framework (Lynn, 1986). There was also a free text box at the end of the survey which prompted SUs to suggest their own items that they felt were relevant. The I-CVI framework used a 4-point scale for relevance from 1 = "not relevant", 2 = "somewhat relevant", 3 = "quite relevant" to 4 = "highly relevant", and similarly for clarity, 1 = "not clear", 2 = "somewhat clear", 3 = "quite clear" to 4 = "highly clear".

After the items were scored by both the SUs and clinicians, items that scored equal to or above 0.75 I-CVI for both relevance and clarity were included in the initial outcome measure. Items with a relevance or clarity score of lower than 0.5 were not included in the measure, and if item scores were between 0.5 and 0.75 for either clarity or relevance the item was reviewed in a workshop with clinicians (n=12) and SUs (n=28). Scale-level CVI (S-CVI), the average of the I-CVIs for all items on the scale, was also calculated for both SU and clinical scoring. The average item quality enables scrutiny of the total relevance of the measure (Polit & Beck, 2006). The acceptable S-CVI scores and the number of experts required to ascertain robust calculations have been debated in the literature, with a recommended number of experts ranging between two and nine, and S-CVI scores between 0.78 and 1 for excellent content validity (Yusoff, 2019). This process enables the finalised set of items to be defined and clinically validated.

Phase 5: Outcome Measure Finalisation

After the SUs and the clinical team completed the content validity process and the scores were calculated, a workshop was held with clinicians to review the wording of the items that achieved a I-CVI score between 0.50 and 0.75. This workshop consisted of expert clinicians discussing each item to determine if it should be kept in the measure or removed and what alternative wording would be appropriate for the item to make it clearer or more relevant for a SST. Once the items were reviewed, a final content validity survey was sent to the original set of clinicians with the finalised wordings to gain the I-CVI and S-CVI scores for the outcome measure.

4.3 Results

This results section is structured in three distinct phases: first, the machine learning modelling outcomes are presented, including feature importance rankings and model performance metrics; second, practitioner interpretations of these findings are examined to validate the clinical relevance of identified predictors; and third, content validity results are reported to establish the robustness of the stigmatised deprivation framework.

4.3.1 Machine Learning Modelling Results

To determine a positive session, a RoBERTa model was applied through the Hugging Face transformer library. This model was used to model patterns between the text and ESQ scores. The outputs were evaluated through a BERT interpreter to extract the parts of the text that were most strongly associated with positive ESQ scores. To identify themes, a CTM was employed to group the parts of text into 10 topics, represented visually as word clouds, each accompanied by a set of phrases to provide more context to each word cloud. These were assessed to formulate an initial collection of 96 potential wants and needs by the practitioners during the workshops; the topic theme and a sample of the initial items are shown in Table 4.1.

Table 4.1: Word Cloud Topics and Initial Measure Item Examples

Word Cloud Topic	**Initial Measure Item Examples (I want to...)**
Improve and build my relationships/Understand more about relationships	Build better relationships with my family Nurture my relationships Improve my relationships
Coping with life/Setbacks in life	Find ways of coping with setbacks Learn how to better manage my distress Learn some new coping tools
To be heard/Understood by others/Acknowledged	Be heard and understood My efforts to be recognised and appreciated Have more fulfilling conversations
Access Support	Understand what professional help will work for me Build a support network Try things out to see what works for me
Understand/Feel better about/express myself	Feel better about myself Be able to concentrate on what makes me feel better Have a better work-life balance
Understand why I feel a certain way (Shame, guilt, fear)	Understand why I feel the way I do Have a space to grieve a loss Feel hopeful for the future
Understand my negative behaviour	Manage my negative behaviour Reduce the harm I am causing myself/others Understand why I hurt myself
Improve my physical health	Have a healthier lifestyle Do activities that improve my physical health Understand how to better manage my physical health condition
Take control	Take control of... Stop struggling with... Make the right decisions
Mindfulness	Work through areas of confusion Learn to relax and be calmer Remember the things I feel grateful for

4.3.2 Content Validity Index Results

The 96 initial item statements that were generated from the 10 word clouds, were presented to clinicians during a workshop and refined into 11 items that represent a range of potential wants and needs that SUs could have when engaging in a SST on a DMHP. The initial 11 items were validated by the SUs who also suggested a range of additional outcome items that would be useful to include within the measure based on their experiences engaging with DMHPs. These suggestions were reviewed and grouped into 4 further items for a total of 15 outcome items (See Table 4.2) before content validity was undertaken by the clinical team. Suggested items included “Learn more about mental health” and “Build a trusted relationship with the practitioner”.

Table 4.2: The Initial 15 Outcome Items

Item #	**Statement pre-chat**	**Statement post-chat**
Item 1	Understand more about my relationships	I now understand more about my relationships
Item 2	Learn about coping strategies	I learnt about coping strategies
Item 3	Feel heard or understood	I felt heard and understood
Item 4	Build my support system	I have found ways to build my support system
Item 5	Be more open to new experiences	I feel more open to new experiences
Item 6	Understand, express or improve my relationship with myself	I feel able to understand, express or improve my relationship with myself
Item 7	Help with grieving a loss	I had help with grieving a loss
Item 8	Understand how to improve my physical health	I understand how to improve my physical health
Item 9	Feel more aligned and progress with my values and intentions	I feel more aligned and am progressing with my values and intentions
Item 10	Work through a specific problem	I worked through a specific problem
Item 11	Feel calmer	I feel calmer
Item 12	Learn more about mental health	I learnt more about mental health
Item 13	Build a trusted relationship with the practitioner	I built a trusted relationship with the practitioner
Item 14	Find a safe, non-judgemental space	I found a safe, non-judgemental space
Item 15	Help overcoming set patterns	I felt helped overcoming set patterns

The I-CVI scores were calculated for both the clinical experts’ and SUs’ surveys. From the clinical I-CVI survey, six items (46.15%) were marked as relevant and clear with I-CVI scores between 0.75 and 1 for both scales. Two items scored below the threshold in the relevance I-CVI but scored highly on clarity (I-CVI = 0.50-0.66). One item scored below the threshold for clarity (I-CVI = 0.50) but highly on relevance. The S-CVI average score for the clinical responses was 0.66 and 0.70 for relevance and clarity. For the SU responses, the S-CVI average scores were 0.70 and 0.63 for relevance and clarity.

4.3.3 CVI Expert Reference Group Workshop

A final workshop was held with an expert panel (n=5) to evaluate the items which attained an I-CVI score of between 0.5 and 0.75 for either relevance or clarity. Each item that did not meet the relevance or clarity threshold was re-assessed, and further wording suggestions were defined. The workshop presented each item alongside the alternative item suggestions; experts were given the option to select an alternative wording, put forward new wording suggestions or remove an item, for example, the item "Build a trusted relationship with the practitioner" was removed from the final list because, according to the experts, this did not seem achievable in a single session. Based on the insight from this final workshop, the items were consolidated into a final list of 13 items which were sent to the original set of clinicians to get the final I-CVI scores for clarity and relevance in preparation for face-validity of the measure.

4.3.4 Finalising Outcome Measure Items

The I-CVI scores were calculated for the final set of items (See Table 4.3). Nine items (84.62%) were marked as relevant and clear, with I-CVI scores between 0.75 and 1 across both scales. Item 1 scored below the threshold in relevance (I-CVI = 0.71) but scored highly in clarity (I-CVI = 0.83). In addition, two items scored below the threshold for clarity (I-CVI = 0.66) but highly on relevance (I-CVI = 0.83); these items were still included in the final measure after the expert panel feedback and will be trialled during face validity testing. The item "Learn more about mental health" was removed after achieving an I-CVI score of 0.66 for both relevance and clarity and, therefore, did not meet the minimum I-CVI score. The average S-CVI score, which is the average of the I-CVIs for all items in the scale was 0.91 for relevance and 0.86 for clarity showing clear evidence that this outcome measure is relevant and clear to both SUs and clinicians when used to understand outcomes in a SST.

Table 4.3: Finalised Items Selected from the Expert Workshops

Item #	**Statement pre-chat**	**Statement post-chat**	**I-CVI Relevance**	**I-CVI Clarity**
Item 1	Discuss and explore how to improve a specific relationship	I have discussed and explored how to improve a specific relationship	0.71	0.83
Item 2	Learn about coping strategies	I learnt about coping strategies	1	1
Item 3	Feel heard or understood	I felt heard and understood	0.83	0.83
Item 4	Build my support system	I have found ways to build my support system	1	0.83
Item 5	Learn how to become more accepting of myself	I have learnt how to become more accepting of myself	0.83	1
Item 6	Help with grieving a loss	I had help with grieving a loss	1	1
Item 7	Understand how my physical and mental health could be linked	I understand how my physical and mental health could be linked	0.83	0.66
Item 8	Understand what my values are and how they could shape my actions	I now understand what my values are and how they could shape my actions	1	0.83
Item 9	Work through a specific problem	I worked through a specific problem	1	0.83
Item 10	Feel calmer	I feel calmer	0.86	0.83
Item 11	Talk about my story or my concerns with someone who is not judgemental	I have been able to talk about my story or my concerns with someone who is not judgemental	0.83	0.66
Item 12	Begin to understand unhelpful patterns of behaviour and how to change them	I have begun to understand unhelpful patterns of behaviour and how to change them	1	1
S-CVI			**0.91**	**0.86**

4.4 Discussion

This study shows the process of developing a single-session outcome measure, the Adult SWAN-OM using contemporary NLP techniques, providing insight into the wide array of SU wants and needs in SSTs on DMHPs. The application of LLMs proved to be informative when evaluating a large corpus of transcripts from a DMHP. This approach enabled the analysis of a significantly larger number of transcripts compared with the manual evaluation of therapeutic transcripts, improving the capacity to extrapolate the wants and needs of SUs. This approach enabled other processes, such as workshops and content validity, to happen sooner by speeding up the initial analysis of transcripts and allowing human resources to focus on other process elements.

The development of a data-informed outcome measure has expanded upon prior outcome measure development methodologies which typically take a participatory and qualitative approach such as focus groups, participatory workshops, semi-structured interviews or the thematic analysis of transcripts (Blais et al., 1999; De Ossorno Garcia et al., 2021; Rose et al., 2011). This qualitative approach to outcome measure development is often limited by the number of focus group or workshop participants, the availability of experts or the number of transcripts that can be analysed and evaluated in the duration of the study. Specifically in the context of SST outcome measure development, (De Ossorno Garcia et al., 2021) conducted expert workshops and manually evaluated a small sample of transcripts to develop the SWAN-OM. The present study expands on this work by evaluating 254 transcripts and conducting participatory workshop sessions with SST experts and SUs to develop the Adult SWAN-OM. This study analyses data from a DMHP which ensures that the findings can be tailored to the nuances of such platforms, offering more targeted and applicable insights compared to studies which use alternative data sources such as text data from social media platforms or online forums (Coppersmith et al., 2018; Schwartz et al., 2016; Zeberga et al., 2022). In comparison, previous studies within the broader application of NLP in mental health have evaluated large samples of text data, such as the examination of 1.53 million geo-tagged tweets (Jaidka et al., 2020) or the analysis of 80,885 conversation transcripts (Althoff et al., 2016b). However, it is noteworthy that these studies primarily concentrate on detecting specific mental health concerns, such as suicide ideation (Oseguera et al., 2017) and the likelihood of depression (Arachchige et al., 2021), rather than evaluating transcript data for SST outcome measure development. In contrast, this work utilises relevant transcript data and co-creation methods to contextualise the model outputs, providing direct insights for therapeutic practice and the development of SST outcome measures.

A challenge in SSTs suggested by (Young & Dryden, 2019) is the increased need for accessible and responsive service delivery. This work provides an outcome measure that has been designed to cover a range of wants and needs via the analysis of representative conversation-level transcript data and co-design methods. This approach has generated an outcome measure representative of a large cohort of DMHP SUs and incorporating their insight during the design of the Adult SWAN-OM should enable accessible and responsive service delivery. In the context of SSTs this work has further illuminated the wide array of desired outcomes for adults participating in SST/OAAT interventions, and that there is a significant range of potential wants and needs. The Adult SWAN-OM enables SUs and practitioners to understand what the SU desires from a single session. (Hymmen et al., 2013) evaluated the effectiveness of the SST delivery model and the outcome measures used to evaluate SSTs, these studies used non-standardised outcome measures, thereby limiting the applicability of SST outcome evaluation. The Adult SWAN-OM was created by specifically evaluating SST transcripts to ensure the outcomes being measured are applicable to the SUs participating in SST, and the outcomes are achievable in a single session, regardless of any potential follow-up sessions the SU may have.

4.4.1 Items Related to Indirect Loneliness Expression

While this chapter primarily focuses on developing an SST outcome measure, it also enables the contextualisation of how the generated items align with the indirect expression identified in Study 1. Three of the 12 finalised items (Items

3, 4 and 7) show clear connections to the patterns of expression identified by practitioners in the previous chapter.

Item 3:"Feel heard or understood" represents the most direct connection to the description of loneliness by practitioners as a core definition provided by practitioners or a core feeling of not feeling connected or understood by others, which is part of the core loneliness experience.

Item 4: "Building my support system" suggests that SU's recognise gaps in their social network, desire to build a non-existent support system or improve an existing social network, which aligns with the conceptualisation of loneliness as the discrepancy between desired and actual social relationships.

Item 7 "Help with grieving a loss" connects to loneliness through the isolation often experienced during bereavement, which was noted by practitioners, as grief frequently triggers loneliness due to both the loss of a close personal relationship and the social withdrawal that often accompanies mourning.

Additionally, Items 14 ("Find a safe, non-judgemental space") and 15 ("Help overcoming set patterns") may indicate loneliness-related concerns. SUs lacking safe social spaces may experience isolation, while those engaging in behaviours that perpetuate loneliness may select items addressing problematic patterns.

4.4.2 Loneliness in Digital Mental Health Interventions

As identified in Chapter 2 subsection 2.6.1, there are a range of approaches such as Cognitive Behavioural Therapy (CBT) (Hickin et al., 2021) or community-based interventions (Alvarez et al., 2025; O'Rourke et al., 2018; Zagic et al., 2022). Several studies have evaluated various digital intervention approaches for reducing loneliness, with varying degrees of success (Alvarez et al., 2025; Borghouts et al., 2021; Bruehlman-Senecal et al., 2020). There is also no specific outcome measure for loneliness in digital mental health interventions. While this study attempts to identify the broader wants and needs of service users at Qwell, there is potential for future work to examine digital intervention outcomes for loneliness specifically.

4.5 Conclusion

A key objective of this study was to create an outcome measure for SSTs on a DMHP, incorporating insights from SUs and clinicians into the design and implementation of the outcome measure. NLP methods were employed to evaluate a large volume of SST transcripts to create an outcome measure that represents the wide range of wants and needs of SUs undertaking SSTs. This has been achieved to a significant degree through the application of LLMs, focus groups and content validity surveys, gathering SU and clinical understanding to improve the relevance and clarity of this outcome measure, ensuring the items are applicable and achievable in a single session.

Including SUs in this process has enabled the creation of an applicable outcome measure, and applying a collaborative and iterative approach to item creation with contemporary machine learning methods demonstrates a strong case for the combination of computational analysis of text data with co-creation methods. A finalised set of 12 outcome items was defined that covers a range of themes that occur in SSTs, including improving relationships, building support systems, and having a safe space to discuss concerns. This work made novel contributions across several fields, including the application of LLMs in the analysis of DMHP transcript data and the development of SST outcome measures by incorporating insights from individuals with lived experience of engaging with DMHPs. Ultimately, this work provides a novel, clear and relevant outcome measure tailored to SSTs.

Importantly, while loneliness was not identified as a direct outcome that service users wish to address, several SWAN-OM items create opportunities for indirect disclosure of loneliness. This finding supports practitioner insights from Study 1, where loneliness was described as highly prevalent yet rarely expressed directly. Instead, SU may select items such as "Feel heard or understood" or "Build my support system" as socially acceptable ways to address underlying loneliness concerns.

4.6 Limitations

A limitation of this study is that these results were generated using a fine-tuned RoBERTa model, the model evaluation metrics suggest that the model may not fully capture the data and could benefit from improvement through the inclusion of more data to enhance result accuracy. Nevertheless, the model used produced satisfactory results and still enabled the creation of this outcome measure; this limitation is mitigated by incorporating co-creation workshops and content validity surveys.

This study's broader relationship to the thesis is slightly limited due to the focus of developing a general outcome measure for a digital mental health intervention rather than a specific outcome measure for loneliness. This was due to the nature of the study, which arose through a collaboration between the University of Nottingham and Kooth. Kooth wanted to collaborate on a research study which would both benefit their research interests and also their intervention platform.

4.7 Future Work

The Adult SWAN-OM has been implemented into the Qwell platform and is currently undergoing further validity testing. This study lays the foundation for future work incorporating LLMs in the analysis of transcript data, providing insight into the elicitation of specific presenting issues.

This work enables further analysis of transcript data as well as other user-generated data from Kooth and Qwell using both traditional classification approaches and LLMs to understand more specific mental health and emotional concerns, such as loneliness.

There is also an ongoing discussion between Nottingham and Kooth to define this intellectual property for use in other digital mental health interventions.

4.8 Ethics Statement

All procedures followed were in accordance with the ethical standards of the responsible committee on human experimentation (institutional and national) and with the Helsinki Declaration of 1964 and its later amendments. Ethics approval for this study was granted by the University of Nottingham Business School (Application ID: 202223018). Service user participants provided written informed consent when participating in the conducted workshops.

4.9 Code Accessibility Statement

Due to the nature of the collaboration between the University of Nottingham and Kooth, the code repository and the raw datasets presented in this chapter are not readily available as they contain information that can compromise the privacy of the research participants. Requests to access the datasets that support the findings of this study should be directed to research@kooth.com.

Chapter 5

Exploring the Independent Impacts of Stigmatised Deprivation on Loneliness

> Loneliness will get you down if you let it, I have heard of loneliness blowing some real fine people's minds; we can't let that happen to you. [*Proceeds to rip the most magnificent blues solo ever recorded*]
> - Albert King Live from the Fabulous Forum (1972)

Abstract

Background

Loneliness and social isolation can be both a cause and symptom of psychological health concerns, in addition to the established negative impacts they have on physical health, employability and educational outcomes. For a multitude of reasons, these phenomena are challenging to evaluate and understand in tandem; this can be attributed to the latent nature of loneliness and the wider sensitivity and stigma surrounding mental health. This study extends such considerations, examining the impact that *stigmatised deprivation*, such

as food and energy insecurity, can have on the prevalence of loneliness across London, UK.

Objectives

The objective of this chapter is to quantify the relative impact of stigmatised deprivation, social support, and environmental factors on loneliness experiences using ML approaches.

Methods

A novel hierarchical ablation machine learning approach is developed, using comprehensive survey data (n=2886) to evaluate the relationship between a wide range of health and economic features and loneliness.

Results

Results indicate that integration of stigmatised forms of deprivation into models, over and above income levels alone, increases loneliness prediction accuracy by 2.38% over baselines, corresponding to potential improvements in understanding of the condition's drivers.

Conclusion

This studies findings demonstrate that stigmatised deprivation, particularly food insecurity, impacts loneliness at an individual level. This not only corroborates previous qualitative research on how stigmatised deprivation affects the experience of loneliness, but emphasises the distinct nature of such challenges versus income deprivation alone.

5.1 Introduction

It has been estimated that over 9 million people in the UK feel lonely either often or all the time (The Campaign to End Loneliness, 2023). Loneliness and its psychological impacts can affect anyone: the young or elderly (Lyyra et al., 2021; Tani et al., 2022; Wenger et al., 1996); those working full-time, part-time or the unemployed (Morrish & Medina-Lara, 2021; Segel-Karpas et al., 2018); those in varied household composition such as living alone or as a single parent (Nowland et al., 2021; Wenger et al., 1996); male, female and non-binary genders (Barreto et al., 2021; Schobin, 2022); those of differing sexual orientations (Gorczynski & Fasoli, 2022; Thunnissen et al., 2022); and people across a range of deprivation levels (Brunner et al., 2012; Elgar et al., 2021; NHS England, 2023; Office for National Statistics, 2023). The phenomenon transcends social boundaries and, according to the *Campaign to End Loneliness*(The Campaign to End Loneliness, 2023), in 2022 49.63% of all adults in the UK (25.99 million people) reported feeling sometimes, often or always lonely, with 7.1% of citizens experiencing loneliness all the time.

Loneliness has been shown to generate a host of negative effects over time. It has serious impacts on the physical and psychological health of individuals (Davis et al., 2023; C. Park et al., 2020); but it can also be highly damaging to the economic conditions of a nation as a whole, with the cost of loneliness to employers recently estimated at more than £2.5 billion per year in the UK alone (Michaelson et al., 2017). Studies also suggest that loneliness is associated with chronic disease and increased mortality rates (Shankar, 2017), with compromised immune functioning and poor cardiovascular health also being related (Valtorta et al., 2016). There is further evidence to suggest that those who are often lonely are more likely are more likely to engage in risky health behaviours such as smoking or substance abuse, although this debate continues (Shankar, 2017).

Although a relationship between deprivation and loneliness has been previously recognised (Brunner et al., 2012; Hernández & Siegel, 2019; Kearns et al., 2015), the exact nature of that relationship and its consequences for the lived experience of loneliness remains underexplored. In particular, while there is a clear link between disposable income and the opportunities for social interaction, far less attention has been paid to specific forms of economic instability. This is perhaps surprising given the impact loneliness has on psychological health (Mushtaq, 2014; Rokach & Patel, 2024), this studies hypothesise that this may be due in part to the *stigma* that surrounds exact forms of deprivation such as *food* and *energy insecurity* (Elgar et al., 2021; Pineau et al., 2021; Swales et al., 2020) which in turn have specific driving affects for loneliness. McNeeley (2012) proposed that the stigma surrounding such conditions exacerbates challenges in eliciting accurate data, as respondents often feel embarrassed or ashamed.

Stigmatised deprivation of this nature is not uncommon: a recent survey of 8630 Londoners published by the Greater London Authority (Greater London Authority, 2022) estimated that not only were 8% of London's population 'often or always' lonely, but that 19% of these respondents were unable to keep their house warm and 18% were forced to use food banks to survive. Of the 26% of London's population that were socially isolated (i.e. not able to rely on someone close to them if they had a serious problem), 40% were also unable to heat their home, and 42% relied on food banks.

Previous work exploring relationships between complex phenomena such as food insecurity and loneliness has either been qualitative, focusing on very specific sub-populations (e.g. old age pensioners, single mothers) (Burris et al., 2021; Fardghassemi & Joffe, 2022; Stack & Meredith, 2018), restricted to investigating the impact of individual variables in isolation (Stack & Meredith, 2018; Tani et al., 2022; Victor & Pikhartova, 2020), or limited to examination of relatively coarse, national-level statistics (albeit still showing strong effect sizes (Elgar et al., 2021)). As such, there is currently limited research examining the impact of food and energy insecurity at individual levels, despite the importance of understanding specific drivers of loneliness to support informed routes to intervention.

This study investigates the impacts of loneliness on *Stigmatised Deprivation*, via a fine-grained, individual-level analysis of loneliness and its potential drivers (both socio-demographic and psychological) based on a new survey of 2,886 respondents across London, UK. Defining this phenomenon as any form of economic insecurity where an individual experiences perceived social exclusion or shame when engaging in support to reduce deprivation impact, this study builds upon the core definition of stigma established by Link and Phelan (2001), and refined by Andersen et al. (2022). Here stigma consists of four key elements: *labelling*, *linguistic separation*, *negative stereotyping*, and *power asymmetry* - all of which appear in food and energy insecurity, with labelling, linguistic separation (e.g. food secure vs food insecure), negative stereotyping (via the mechanism of social exclusion (Pineau et al., 2021; Reutter et al., 2009)) and experience of power asymmetry due to reliance on social support (food banks, free school meals or universal credit).

This work aims to quantitatively extend hypotheses generated in the previously discussed qualitative studies, by first isolating individual forms of stigmatised deprivation from general deprivation scores and then setting these features against contextual factors such as socio-demographic, behavioural and environmental variables. AI-modelling is then used to analyse the relationship between variables and loneliness. This modelling approach allows researchers to consider whether food and energy insecurity are symptoms of a more general psychological experience of deprivation, or identify whether the effects of food and energy insecurity hold specific driving effects, given the stigmatised nature of these features. Specifically, the applied AI-modelling approach enables the analysis of the granular effects of these features over traditional statistical approaches such as linear regression and structural equation modelling, which typically examine variables in isolation and cannot adequately capture the complex interactions between multiple socio-environmental factors that may moderate the relationship between stigmatised deprivation and loneliness.

Do those, for example, who experience less social cohesion, differing geographical locations, varying access to public transport, limited access to green space and/or living conditions in highly dense populations suffer effects differently (Astell-Burt et al., 2022; Bergefurt et al., 2019; Laustsen et al., 2024; Victor & Pikhartova, 2020; Williams et al., 2024) in particular, this study asks:

1. Can food and energy insecurity impact loneliness at an individual level?

2. Does this impact occur in addition to the relationships with income?

3. Are effects moderated or co-occurring with other social features (i.e. variables that can moderate or exacerbate that relationship)?

This chapter addresses these research questions by quantifying the relative impact of stigmatised deprivation, social support, and environmental factors on loneliness experiences using machine learning (ML) approaches. The objective is to identify which forms of deprivation carry particular stigma and examine how these stigmatised experiences independently contribute to loneliness beyond traditional sociodemographic predictors.

5.2 Background

Loneliness is defined as the subjective perception of a discrepancy between the desired and true social relationships in terms of companionship, connectivity, or intimacy (Hawkley & Cacioppo, 2010). This study focuses on the subjective emotional experience of loneliness, i.e. the experiences associated with loneliness defined by Weiss (1975), rather than the objective experience of how often people are alone. The nuances in the experience of loneliness make it difficult to measure, and over time loneliness can have a number of serious negative effects, impacting physical and mental health outcomes (Davis et al., 2023; C. Park et al., 2020) while remaining latent. Furthermore, acquiring accurate estimates is difficult due to the stigma associated with loneliness and its prevalence being higher in poorer areas (Cheetham et al., 2019; Kung et al., 2022).

Despite these challenges, loneliness is still a highly prevalent issue, with the UK Government producing a range of reports showing the negative effects of loneliness across the population (Department for Digital, Culture, Media and Sport, 2018, 2023; Office for National Statistics, 2024; U. K., 2020, 2021, 2022). These reports show how loneliness has been linked to earlier deaths on a par with smoking or obesity, increased risk of coronary heart disease, stroke, depression, cognitive decline and an increased risk of Alzheimer's disease (Department for Digital, Culture, Media and Sport, 2018). Studies typically focus on specific population subgroups, including university students, patients presenting at GP practices with comorbidities, and elderly residents in care homes (Altschul et al., 2021; Gerino et al., 2017; Reedman-Flint et al., 2022). There are some limited examples of successful community interventions implemented by the UK government (such as community gardening and community space initiatives) that enable communities to engage via social prescribing (Department for Digital, Culture, Media and Sport, 2023), which reduces feelings of social isolation and loneliness. However, 'Public opinions and social trends, Great Britain: personal well-being and loneliness', a dataset published by the Office of National Statistics (ONS), reports a range of social trends show a steady increase in self-reported loneliness over time (see Figure 5.1).

This steady increase in loneliness is likely due to strong links between loneliness and social infrastructures. Factors such as poor access to housing, transportation, limited access to green space and increasing deprivation limit social cohesion, combined with limited social support and weakened economic opportunities, which have a deleterious effect on experienced loneliness (J. Wang et al., 2018). This is particularly pertinent as social support and provision continue to stagnate and decline in the UK while mental health concerns endure and rise(Kung et al., 2022; Shields & Price, 2005). This relationship between

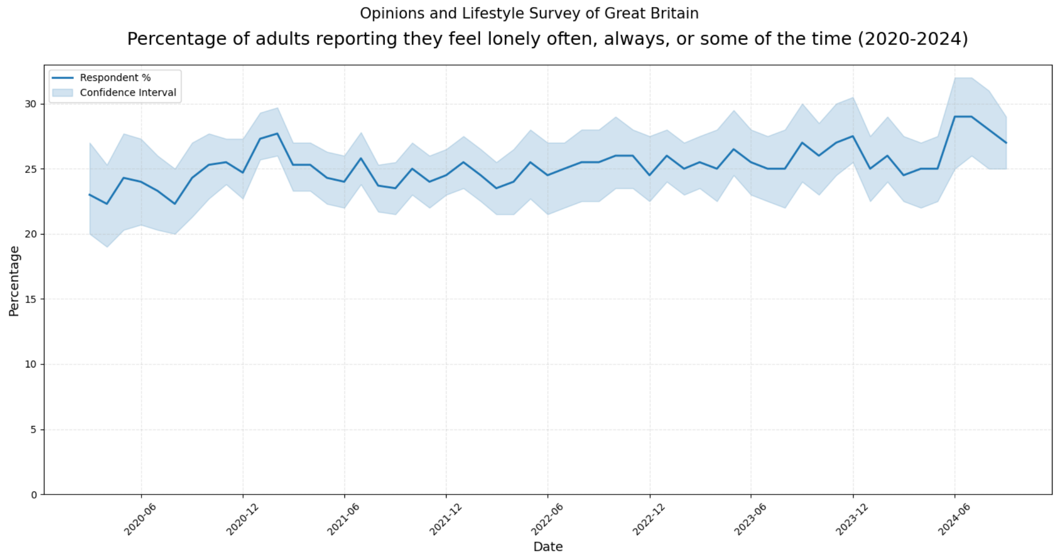

Figure 5.1: *Public opinions and social trends, Great Britain: personal well-being and loneliness (October 2021 - September 2024)*

loneliness and social infrastructures is a concern that the UK Government has acknowledged in 2023 (Department for Digital, Culture, Media and Sport, 2023), finding the factors that contribute towards loneliness include physical health, deprivation and social care provisions. Deprivation can manifest itself in several ways, whether food and energy security are present or not; it is not just a lack of income that leads to deprivation but the consequences of an increased cost of living which enables this cycle of deteriorating physical and mental health.

Food insecurity has serious long-term health consequences, including inadequate nutrient intake, diet-related chronic disease, and magnified physical and mental health issues (Nica-Avram et al., 2021). The financial hardship commonly experienced by those in food insecurity also limits their ability to socialise, leading to feelings of social isolation (Stack & Meredith, 2018). A 2023 ONS report found that adults reporting 'moderate-to-severe' depressive symptoms were over three times more likely to report experiencing food insecurity than adults with 'no-to-mild' depressive symptoms(Office for National Statistics, 2023). The mental health consequences of food insecurity are known to be highly sensitive to social contexts, Elgar et al. (2021) concludes that the psychological health consequences of food insecurity are nuanced and moderated by a range of variables. In settings where food insecurity is less common and potentially more stigmatised, there are increased mental health consequences. As such, identifying which factors increase a person's propensity to loneliness and how behavioural, environmental, and demographic variables interact to moderate this relationship is important for creating more effective governmental policies, thereby increasing the efficiency and efficacy of assigned resources to reduce loneliness.

The relationship between food insecurity and loneliness (Burris et al., 2021) is also not unique, as loneliness co-occurs with other forms of deprivation. Energy insecurity is a concept that reflects hardships with the cost and quality of household energy and is defined as the inability to meet basic household energy needs (Jenkins et al., 2016). Several studies show the relationship between energy insecurity and social isolation (Brunner et al., 2012; Hernández, 2016; Hernández & Siegel, 2019; A. Jones, Februray 2022; Office for National Statistics, 2023). Energy insecurity results in increased feelings of anxiety, depression, stress, and worry about keeping warm (Hernández, 2016). Those facing energy insecurity feel social stigma about their economic hardship, which in turn exacerbates conditions of social disadvantage. A 2023 ONS report (Office for National Statistics, 2023) found that adults reporting moderate-to-severe depressive symptoms were over twice as likely to experience energy insecurity as adults with no-to-mild symptoms. There is a clear connection between deprivation and loneliness; however, it is still unclear whether these are symptoms of a more general, psychological experience of deprivation or whether the effects of food and energy insecurity (particularly stigma) hold specific driving effects.

There is limited research into the application of machine learning (ML) models to understand the features that impact loneliness. This research gap is two-fold, methodological approaches typically rely on qualitative methods or a lack of quantitative approaches that elicit the features that impact loneliness.

due to studies primarily looking at ageing populations, the generalisability of the findings is limited. There is a range of data that can be evaluated to understand loneliness. Methods involve the statistical analysis of self-reported survey data, although the application of Natural Language Processing (NLP) methods to evaluate elicitations of loneliness in text data has proliferated. Typically, these text data are generated on social media platforms such as X (previously Twitter) or Reddit (Andy, 2021; Guntuku et al., 2019; Koh & Liew, 2022; Ng et al., 2023). Other data streams include sensing technologies, including smartphones, Fitbit and Bluetooth data (Doryab et al., 2019; Site, Lohan, et al., 2022; C. Wu et al., 2021).

Ejlskov et al. (2018) found that positive wellbeing, an absence of health problems and being married were strong predictors of lower loneliness using Random Forest (RF) methods to understand the relationships between 49 covariants and loneliness in individuals aged 68 or above. Kearns et al. (2015) applied multinomial linear regression on cross-sectional survey data to understand loneliness and deprivation, finding that feelings of social connectedness and the ability to rely on family and friends reduce feelings of loneliness while stressors such as deprivation, crime rates and poor governmental social support increased experiences of loneliness. Altschul et al. (2021) applied Gradient-boosted modelling to understand the difference in predictors of loneliness amongst two age groups, 45-69 and 70-79 years of age, finding that emotional stability and household composition (living alone) contributed towards experiences of loneliness. Structural equation modelling (SEM) has been applied to show the relationship between stress and loneliness to be bidirectional over time (Laustsen et al., 2024), while Gerino et al. (2017) found loneliness influences mental health and physical quality of life in Italian adults aged 65–90.

5.3 Methodology

5.3.1 Data Sample and Procedure

Ground-truth data concerning loneliness were collected for the study via a survey disseminated to participants across 82.7% of London's geographical extent, UK. To ensure adequate coverage of economically secure and insecure participants, participants were drawn from the food-sharing platform *Olio*, which has over 7 million registered users worldwide and is active across 51 countries as of 2023. The platform allows its users to list food or household items that they want to give away via their mobile device, to reduce waste and allow other users to request and then collect said items.

The survey was delivered to London-based users via a mobile-app, and completed by (n=2,886) participants in Greater London between 22nd November 2022 and 5th December 2022. Respondents received a £5 reward for completing the survey. A careful survey sampling strategy was applied, implementing quota restraints for socioeconomic status, as informed by the Indices of Multiple Deprivation (IMD) score of respondents' home areas (where the user was registered), defined as one of the 983 administrative areas of London, called MSOAs (See Figure 5.2)[1] and based on activity on the Olio Platform, participants had to have been active on the platform in the 6 months prior to data collection.

[1]Middle Layer Super Output Areas (MSOAs) are a geographic hierarchy designed to improve the reporting of small area statistics in England and Wales, and on average a neighbourhood of 2,000 households with an average population size of 7,800

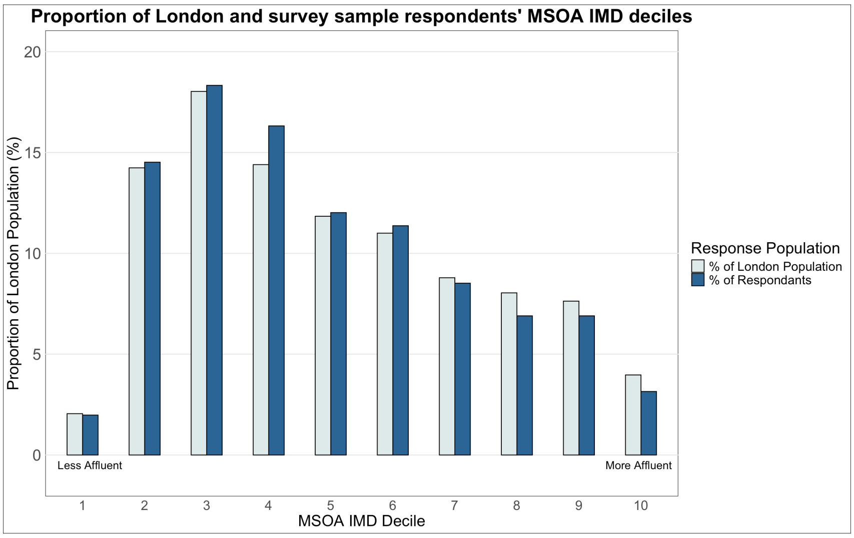

Figure 5.2: *Proportion of survey sample respondents compared to Proportion of London and survey sample respondents' MSOA IMD deciles from 1 (most deprived) to 10 (least deprived)*

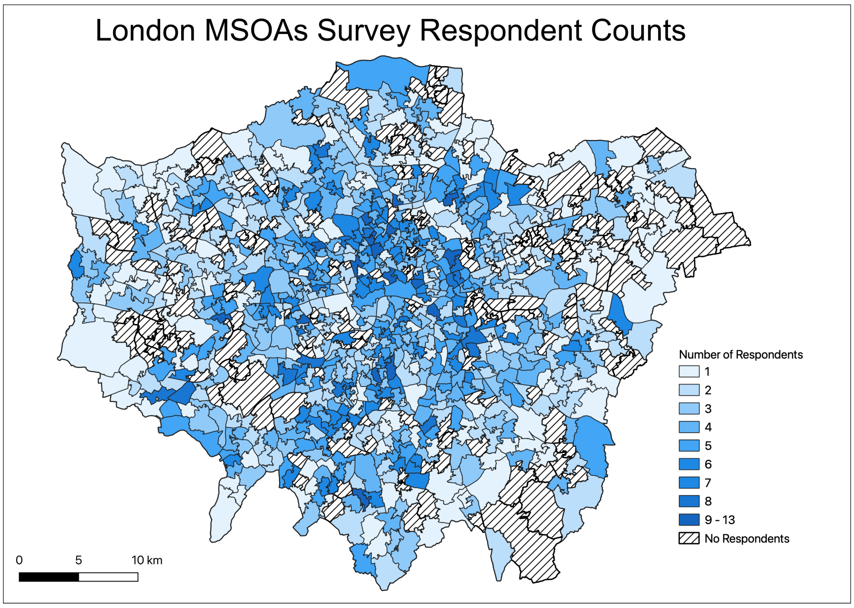

Figure 5.3: *Visualisation of the distribution of survey respondents across London's Middle Super Output Areas (MSOAs). Darker shades indicate higher response rates.*

5.3.2 Measures

The survey primarily captured insight across three themes: food insecurity via the USDA Food Security Survey Module, energy insecurity via the 2015 Residential Energy Consumption Survey (RECS) (Harker Steele & Bergstrom, 2021), and Loneliness from the three-item Revised UCLA Loneliness Scale (Hughes et al., 2004). Demographic questions were also included to capture information related to income, age, household composition and employment. The full list of survey questions can is shown in Appendix B.

Two approaches are typically used when measuring loneliness: direct and indirect measurement. Direct measures make specific reference to loneliness i.e. *How often do you feel lonely?* (Mund et al., 2022; D. Russell, 1982). Direct loneliness measures are often composed of a single item, in comparison to indirect measures which use a range of questions related to a respondent's subjective social experience *How often do you feel that you lack companionship?* or *How often do you feel isolated from others?* (Shiovitz-Ezra & Ayalon, 2012).

The revised UCLA Loneliness scale was selected following the UK government's recommended approach as suggested by the ONS (Office for National Statistics, 2018a). In order to keep survey completion time to a reasonable duration, a subset of questions was included from this scale. The measures 'How often do you feel left out?' and 'How often do you feel isolated from others?' were merged into the question *'How often do you feel isolated from others/left out?'*, as suggested by an independent UK government report on loneliness that found that respondents often interpreted the question 'How often do you feel that you lack companionship?' differently (Office for National Statistics, 2018b).

The authors note that this varies from the ONS practice of using the 3-item UCLA loneliness scale, plus a single direct loneliness question. However, due to the sensitive nature of the survey and its relationship to stigmatised insecurity measures, it was felt to be inappropriate to ask a direct loneliness question which also accounts for the suggestions by McNeeley (McNeeley, 2012) about conducting surveys around sensitive topics. The full survey questions can be seen in the supplementary material.

A composite score of loneliness was calculated by assigning a numerical value to the responses for the two retained UCLA Loneliness Scale questions (Hardly ever or never = 1, Some of the time = 2, Often or always = 3) and computing a loneliness score of between 2 and 6 (See Figure 5.5). A binary feature, 'Loneliness', was assigned to respondents based on their composite score; those respondents with scores of 4 and less were classified as 'Not Lonely', while those with scores of 5 and above were classified as 'Lonely'.

5.3.3 Feature Engineering and Selection

An array of ML models were optimised to classify participants, employing 21 features identified in Table 5.1 across two broad domains (socioeconomic and environmental). Variable Importance analysis was then used to elicit relationships identified by optimal models. In this study, independent variables (features) were drawn from a range of prior literature reflecting the socioeconomic and environmental factors that an individual encounters throughout life:

- **Environmental Variables:** geospatial features that represent the neighbourhood characteristics of a participant's home area, which were gathered through open government data from the ONS or Transport for London (TfL) and linked via a geospatial lookup.

- **Socioeconomic Variables:** reflecting a range of individual features including income, deprivation, age, household composition, employment status, and education, self-reported within the survey.

Table 5.1: List of features generated from the self-reported survey and national data sources

Feature	Data source	Description
Environmental		
Indices of Multiple Deprivation (IMD) Score	ONS	Poverty ranking as defined by the IMD score provided by the UK ONS
Living Environment Score	ONS	Living environment score as defined by the UK Office of National Statistics
Population Density	ONS	Population density of the respondents LSOA
Bus/coach Linkage	Geospatial	Distance from the LSOA to the nearest bus/coach stop
Tram/Metro/ Linkage	Geospatial	Distance from the LSOA to the nearest tram/metro access
Rail Linkage	Geospatial	Distance from the LSOA to the nearest train station
Access to Green Space	Geospatial	Distance in meters from the closest green space
Socioeconomic		
Unable to Rely on Friends and Family	Survey	The degree to which the respondent can turn to friends and family when in need
Financial Anxiety	Survey	Extent of worry about housing/rent payments
Unemployed	Survey	Whether the individual considers themselves unemployed
Not Working (Looking After Child or House)	Survey	Whether the individual's ability to work is impacted by caring responsibilities
Disability	Survey	Whether the individual's ability to work is impacted by disability
Gender	Survey	The reported gender of the participant
Physical or Mental health Conditions/Illnesses	Survey	Self-reporting of ongoing illness, physical or mental health problems
Household Composition	Survey	Single/living alone with children (under 18)
Energy Insecurity	Survey	The degree to which the individual struggles to pay for fuel/energy
Food Insecurity	Survey	The degree to which the individual struggles to pay for food/meals
Food bank usage	Survey	If the respondent has needed to use a food bank
Energy Anxiety	Survey	Self-reported concern/worry about their ability to pay for energy
Income	Survey	Self-reported income range of the participant

5.3.4 Modelling Approach

In order to investigate the array of factors impacting loneliness, while also allowing for a range of moderating interactions between variables, a non-parametric framework was selected. Analysis was structured around a binary classification task, optimising random forest models to predict individuals as lonely or not-lonely based on a potential set of 21 input covariates (features) as described in Table 5.1. To understand the impact of key features and to ascertain their incremental benefits in assisting the prediction of loneliness, a systematic, novel hierarchical ablation modelling approach was developed. Level-1 models used all 21 available features. Level-2 models used 20 available features, omitting either food insecurity (Level-2a) or energy insecurity (Level-2b) from the dataset. Finally, Level-3 models used 19 features, omitting both stigmatised deprivation variables.

For each level, data was randomly assigned into training (70%) and test (30%)

sets prior to model investigation. Random Forest models were then rigorously optimised via a 5-fold cross-validation approach, grid searching across model hyperparameters (*no. of estimators, maximum depth, splitting criterion, maximum features used in each tree, and minimum sample splitting for nodes*). A mean validation accuracy metric was used to obtain an optimal parameterisation, which was then used on the full training set to produces a best-of-class model for that level. Finally, classification accuracy was measured on the held-out test set.

All levels were trained using the same datapoints. To account for class imbalance, these were sampled from the full data to form a stratified set of 1000 observations (500 lonely observations and 500 non-lonely observations). Downsampling was preferred on this occasion to oversampling methods (such as SMOTE) in order to avoid the use of synthetic datapoints. Approaches such as SMOTE can be highly useful in situations with well-defined feature distributions (Joloudari et al., 2023), but can add risk of overfitting - and generate challenges in interpretation of model predictions (synthetics being less representative of real-world observations), a factor potentially important in domains such as health and social care (Wongvorachan et al., 2023). This full approach is illustrated in Figure 5.4.

To ensure robust results and account for the stochastic nature of non-parametric modelling using Random Forests, the complete experiment was re-run 5 times. Each iteration of the experiment utilised a different random seed, kept consistent across hierarchical-levels analysed in each iteration. This resulted in a total of 20 models, 5 for each hierarchical-level. To assess models produced at each level, and hence the independent impact of stigmatised deprivation variable, accuracy losses were analysed against the base model (level-1). A Friedman test was applied to identify significant differences in performance (and model accuracy distributions), with a *post-hoc* pairwise comparison being applied via a Bonferroni-corrected Wilcoxon signed-rank test. A Friedman test was selected due to the non-normal distribution of the model accuracies.

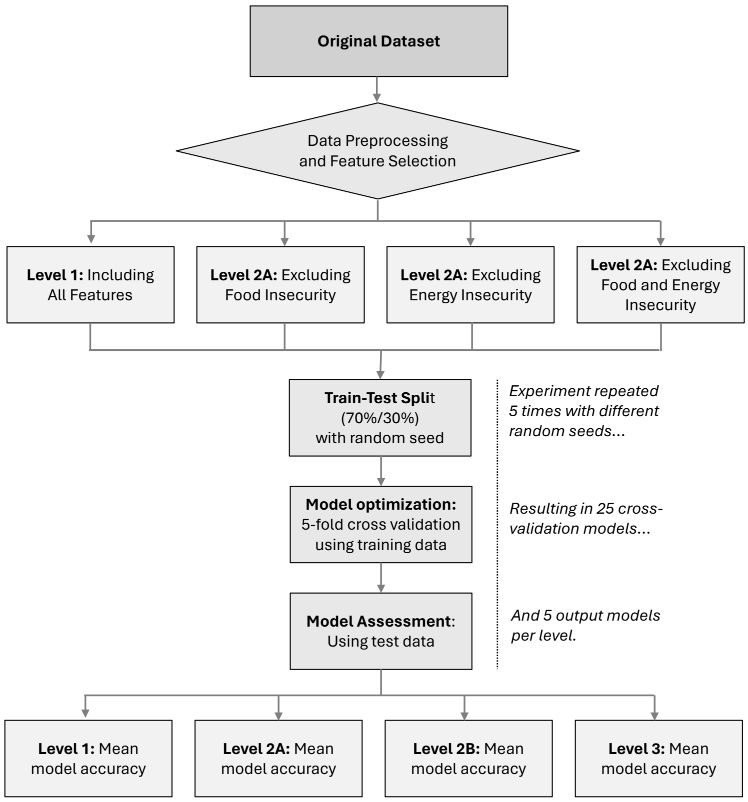

Figure 5.4: *Hierarchical Ablation modelling workflow, comparing four model versions (Level-1: all features, Level-2A: no food insecurity, Level-2B: no energy insecurity, Level-3: no food or energy insecurity). Each level has 25 models produced during cross-validation, and 5 optimised output models that are tested.*

5.3.5 Variable Importance Analysis

A non-parametric ML approach was then used to understand feature importance and interaction effects between covariates without explicit *a priori* definition of their relationships (which can be challenging in traditional techniques such as SEMs). This approach provides the capacity to apply advanced feature importance methods to resulting models alongside SHapley Additive exPlanations (SHAP) analysis. Random forest models, in particular, allow the use of Model Class Reliance (MCR) analysis (Smith et al., 2020), a recently developed variable importance method that can provide deeper insights into the impacts variables have on predicting loneliness. When discussing the potential application of ML methods to understanding psychological phenomena, Yarkoni and Westfall (2017), emphasised the need for explainability of models. However, running variable importance tools such as SHAP on one arbitrary model can generate misleading results due to i. the stochastic nature of ML algorithms; and ii. The fact that different, equally-performing models can arbitrarily use different feature combinations to generate the exact same prediction accuracy. Which model's explanation is 'correct' is unclear.

The MCR approach was introduced by Fisher et al. (2019) to address this challenge, computing feature importance *bounds* across *all* optimal models (called the 'Rashomon Set') rather than for a single model solution alone. This is useful in investigating psychological phenomena, where direct observations themselves are not possible and proxy drivers must be examined. MCR was utilised to compute the permutation feature importance bounds each of our input variables had in predicting loneliness; calculating the minimum (**MCR-**) and maximum (**MCR+**) impact each feature can have on prediction accuracy, across all instances of the model class. While initially implemented for use with support vector machines, Smith et al. (2020) adapted MCR to random forest classifiers and regressors. In this study, this study extends Smith's work for use with hierarchical modelling, following a similar ablation approach used in Dolan et al. (2023). To understand the contribution of independent variables in each level, the optimal model across all experiments was identified, and both SHAP values and MCR importance bounds were calculated. MCR and SHAP plots were then used to assess which features contribute the most towards the model prediction of loneliness.

5.3.6 Code Availability

The complete code for data preprocessing, machine learning models, and analysis presented in this chapter is available at: https://github.com/GregorMilliganUoN/Exploring-the-Independent-Impacts-of-Stigmatised-Deprivation-on-Loneliness. The repository includes all the code notebooks necessary to reproduce the hierarchical ablation modelling approach and feature importance analysis.

5.4 Results

5.4.1 Survey Results

The results of the survey reflect data published by NHS England (NHS England, 2023), showing that those who are in areas with the lowest IMD Deciles (those who are more deprived) report being often or always lonely more than those in the higher deciles. Furthermore, the relationship between more severe loneliness and food insecurity, energy insecurity, poorer health and foodbank usage identified by the GLA's survey of London (Greater London Authority, 2022) is also reflected in the survey data (See Figures 5.8, 5.9, 5.10).

Analysis of the composite loneliness scores revealed that 20.9% of respondents (n = 590) were identified as lonely, while 79.1% (n = 2232) were not (see Figure 5.6). Results support conclusions drawn by NHS England (NHS England, 2023), reporting that those who are in areas with the lowest IMD Deciles (those who are more deprived) report being often or always lonely more than those in the higher deciles. A clear socioeconomic gradient emerged in our data, with a higher prevalence of loneliness in less affluent areas characterised by lower IMD scores (see Figure 5.7).

A relationship between more severe loneliness and food insecurity, energy insecurity, poorer health and foodbank usage proposed within the Greater London Authority survey of London (Greater London Authority, 2022) is also reflected in the survey data (See Figures 5.8, 5.9, 5.10). The association between deprivation and loneliness was particularly pronounced when examining stigmatised deprivation variables. Among respondents classified as having very low food security, 77.4% (n=359) reported feeling lonely (See Figure 5.8); whereas 85.6%(n=88) of those experiencing very low energy security also reported loneliness (See Figure 5.9).

Figure 5.11 presents the proportion of loneliness across age groups. The youngest cohort (18-24 years) exhibits the highest prevalence of loneliness (25.5%), while those aged 65+ show the lowest (13.7%, n=95). The relatively consistent loneliness rates across middle age groups (19-22%) suggest that loneliness is pervasive across the lifespan and may be driven by factors beyond age alone.

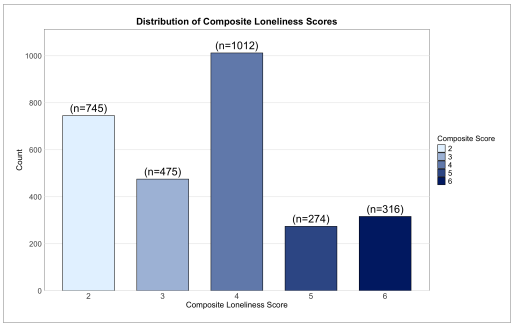

Figure 5.5: *Composite loneliness scores range from 2 (lowest) to 6 (highest), representing increasing levels of loneliness.*

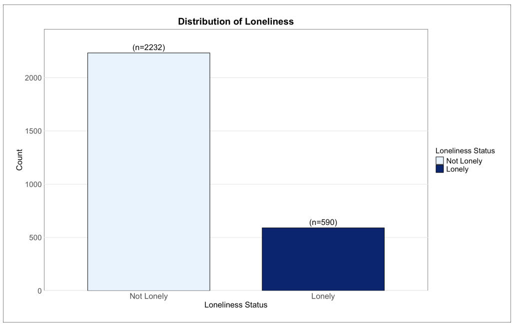

Figure 5.6: *Distribution of Lonely vs Not Lonely Respondents*

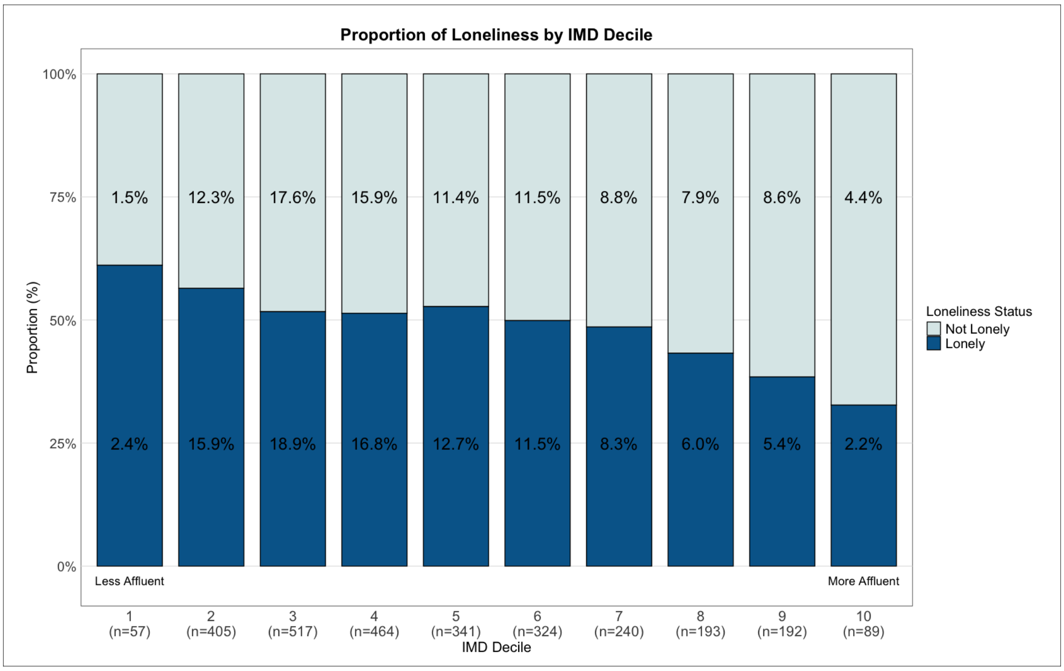

Figure 5.7: *IMD deciles disaggregated by Loneliness. Lower IMD deciles represent less affluent individuals and higher IMD deciles represent more affluent individuals.*

5.4.2 Modelling Results

This analysis compared four treatment levels to evaluate how different stigmatised deprivation features impact the prediction of loneliness. For treatment 1 (Level-1) the optimal treatment for level-1 had a mean test accuracy score of

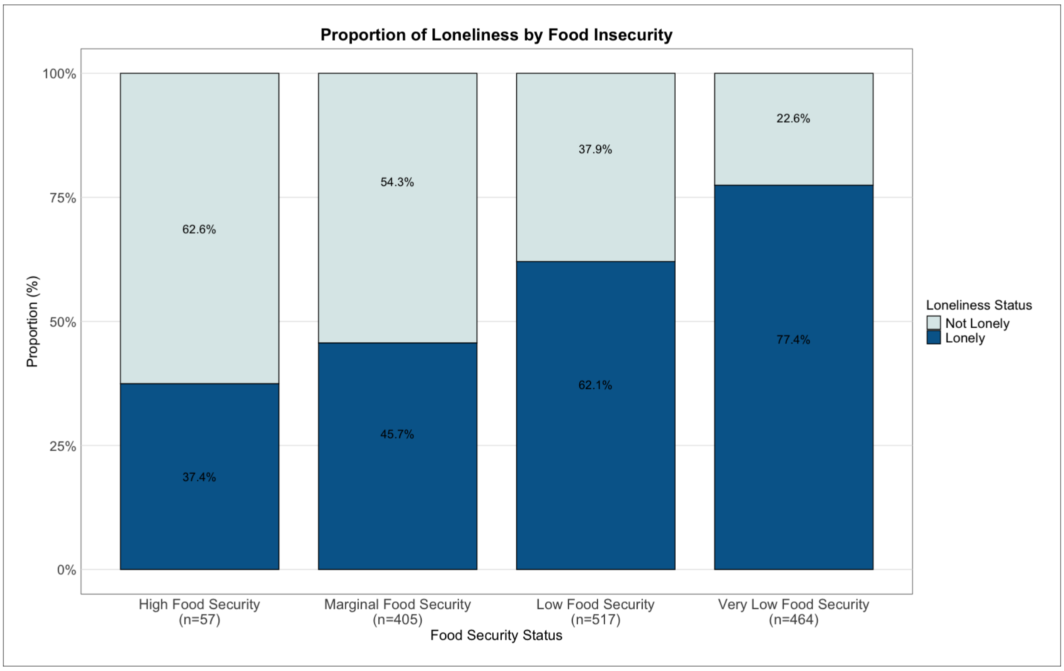

Figure 5.8: *Association between food security status and loneliness. The proportion of loneliness increased with worsening food security status, from high food security to very low food security.*

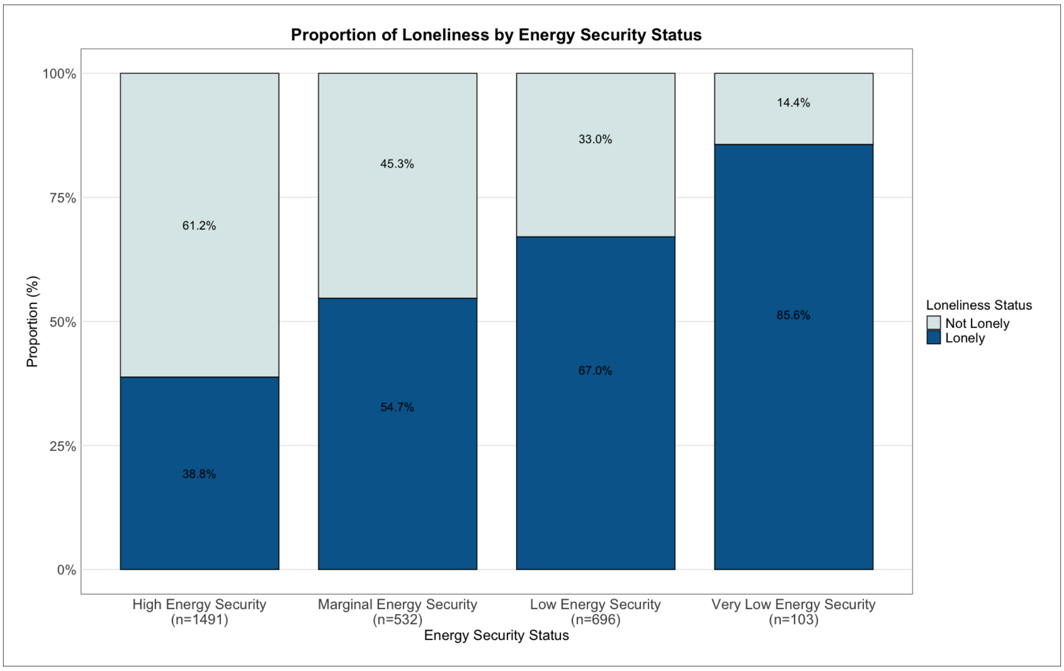

Figure 5.9: *Association between energy security status and loneliness. The proportion of loneliness increased with worsening energy security status, from high energy security to very low energy security.*

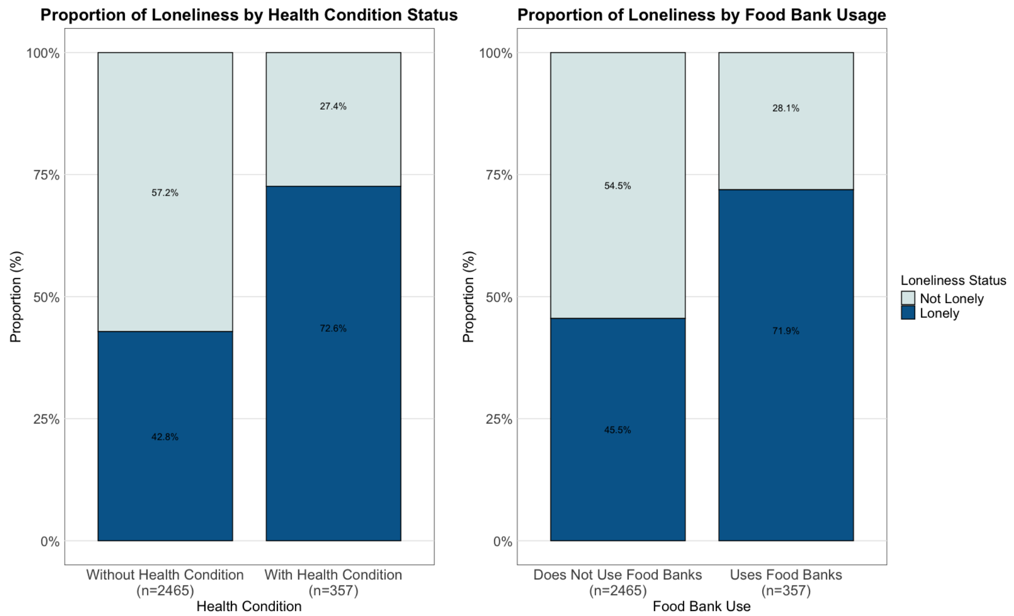

Figure 5.10: *Comparison of loneliness proportions across health conditions and food bank usage. The left panel shows health conditions disaggregated by loneliness. The right panel shows food bank usage disaggregated by loneliness.*

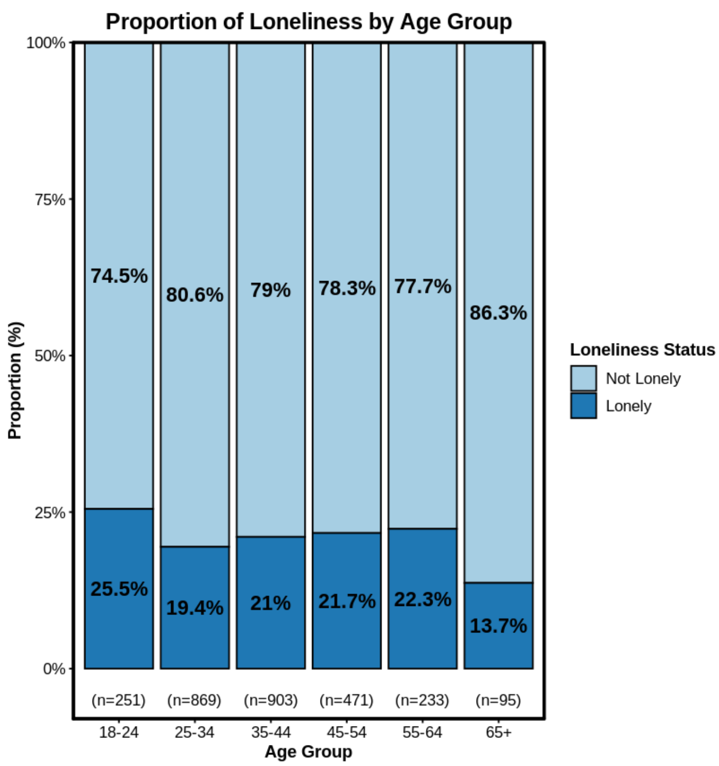

Figure 5.11: *Comparison of loneliness proportions across age groups.*

69.6%; for treatment 2 (Level 2-A), with *food insecurity* excluded, the mean test accuracy of the treatment decreased to 68.2%; for treatment 3 (level 2-B), with *Energy Insecurity* excluded, the test accuracy of the treatment differed less, achieving a score of 69.3%. For treatment 4 (Level-3), where both *Food and Energy Insecurity* were excluded, the mean test accuracy of the model dropped to 67.3% - reflecting a 2.32% drop in predictive power.

To assess if the unique role of energy and food insecurity was significant, A Friedman test was applied, revealing significant differences across levels ($\chi^2(3) = 12.97$, $p = .002$). Post-hoc analysis using Wilcoxon signed-rank tests with Bonferroni correction ($\alpha = .0083$) showed significant differences between Level-1/Level-2A, Level-1/Level-3, Level-2A/Level-2B, and Level-2B/Level-3 pairs (See Table 5.3 and Table 5.4). These findings indicate that removing stigmatised deprivation features (particularly in Level-2 and Level-3) had a substantial negative impact on model performance compared to Level-1, while Level-2B maintained relatively similar performance levels to the base model. This indicates that some food insecurity holds greater informational content over energy insecurity alone in predicting loneliness, but that both hold unique explanatory strength over and above basic deprivation statistics.

Table 5.2: Model Performance Summary: Comparative Analysis of Treatment Models Against Base Configuration

Treatment Level	**Mean CV Accuracy%**	**Highest Test Accuracy%**	**Mean Test Accuracy%**	**Accuracy Loss from Baseline%**
Level 1	70.24	73.63	**69.60**	0.00
Level 2A	69.59	71.33	**68.24**	-1.36
Level 2B	70.68	71.00	**69.28**	-0.32
Level 3	69.41	70.33	**67.28**	-2.32

Note. CV (Cross-Validation). Complete model results, including model parameters, are provided in the supplementary material.

Table 5.3: Results of Friedman Test

Analysis Type	**Test Statistics**
Friedman Test	$\chi^2(3) = 12.97$, $p = .002$

Table 5.4: Post-hoc Pairwise Comparisons Using Wilcoxon Signed-Rank Tests

Comparison	**Z-score**	**Effect Size (r)**	***p*-value**
Level 1 vs. Level 2A	−3.84	0.54	$< .001^{***}$
Level 1 vs. Level 2B	−1.18	0.17	.239
Level 1 vs. Level 3	−4.93	0.70	$< .001^{***}$
Level 2A vs. Level 2B	−2.81	0.40	$.005^{**}$
Level 2A 1 vs. Level 3	−1.75	0.25	.080
Level 2B vs. Level 3	−4.10	0.58	$< .001^{***}$

Note. Significance levels: $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$
Bonferroni-adjusted alpha level = .0083

Across all models, features related to stigmatised deprivation are shown to contribute towards the prediction of loneliness. While income and income-related worry played a role in predicting loneliness, the inclusion of more granular deprivation features, particularly food insecurity, aid in increasing model accuracy. These findings raise important questions about the relationship between specific forms of deprivation and loneliness, which is explored in detail in the following discussion.

5.5 Discussions

Both SHAP and MCR analysis was used to unpack the drivers of these results. Plots for Level-1 (Figure 5.12) showed that the features contributing to accurate loneliness predictions the most were *unable to turn to friends and family*, *food insecurity*, *illness* and *energy insecurity*. The **MCR+** and **MCR-** values for *Food insecurity* are larger than *illness*, which shows that across all the MCR treatment evaluations, *food insecurity* was a better predictor of loneliness than *illness*. The SHAP plot (Figure 5.12) for Level-1 indicates the directionality of the feature in the context of a positive prediction of loneliness; being unable to turn to friends and family contributes towards a positive prediction of loneliness. Other contributing features included *income* and *worry about energy payment*. Some feature impacts are context-dependent, as evidenced by the SHAP plot for features such as *distance to railway access*, which shows no clear directionality in predicting loneliness. This suggests possible interaction effects with other features or a non-linear relationship with the target variable, creating less discernible SHAP distributions.

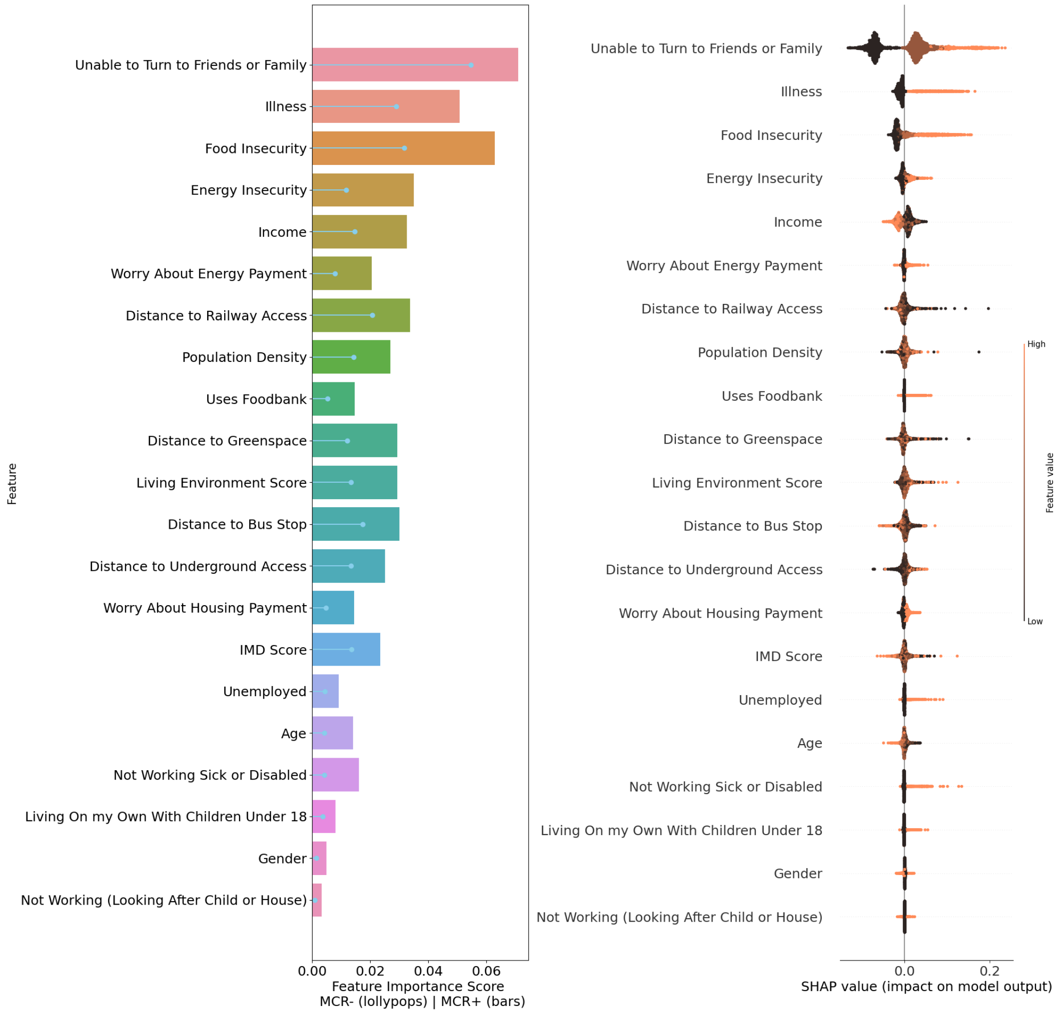

Figure 5.12: *Base Model MCR and SHAP Plots for All Features. The left plot displays minimum (**MCR-**) and maximum (**MCR+**) feature values across optimal models. The right plot shows SHAP summary results for the top 20 predictive features, with point position indicating SHAP value magnitude and direction, and colour representing feature value intensity.*

Evaluating the MCR and SHAP plots for Level-2A, *unable to turn to friends and family* and *illness* still remain the highest contributing features. However, there were changes in the subsequent contributing features, including *energy insecurity*, *Income* and *population density*, suggesting an increase in their impact on the model prediction (See Figure 5.13). The minimum MCR value for *income* and *illness* is higher than that of *energy insecurity* showing that income has a higher minimum impact on the prediction of loneliness.

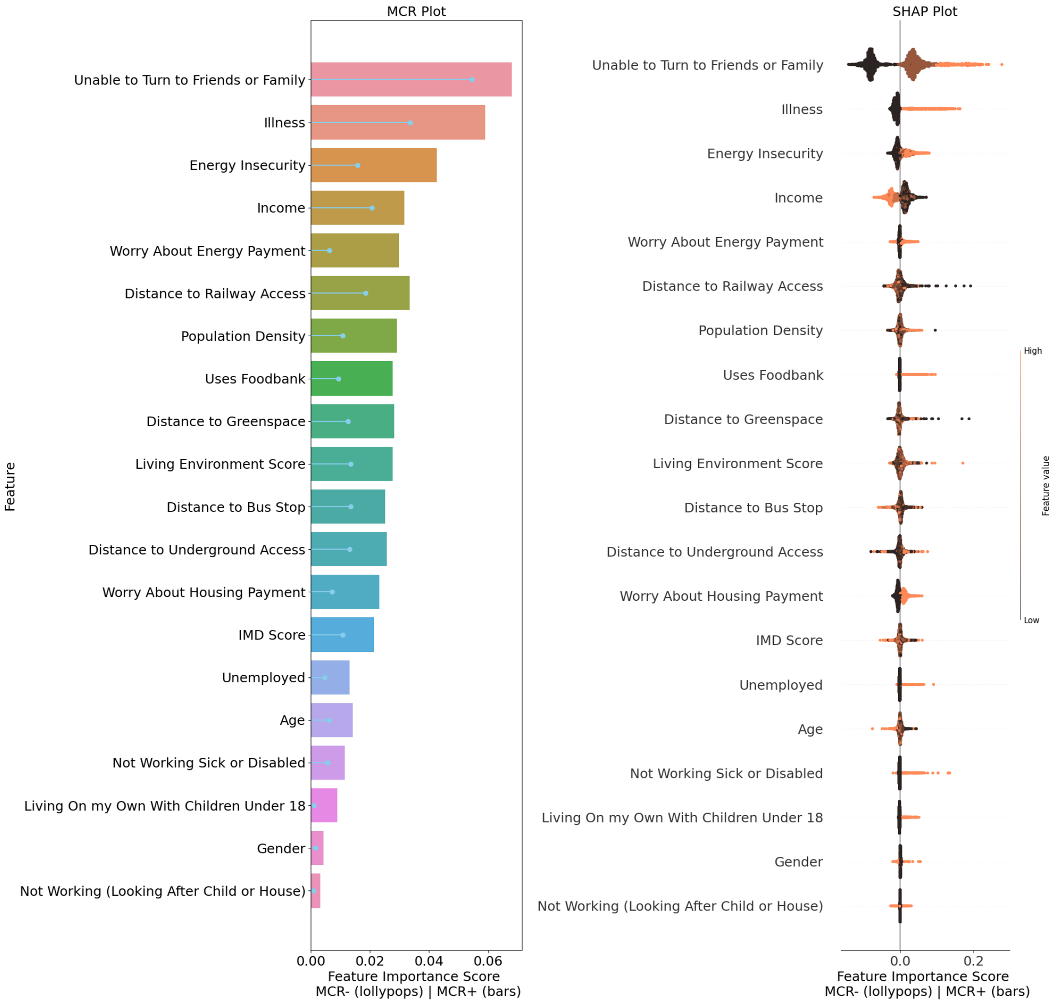

Figure 5.13: *Model 1(Excluding Food Insecurity): MCR and SHAP plots. The left plot displays minimum (**MCR-**) and maximum (**MCR+**) feature values across optimal models. The right plot shows SHAP summary results for the top 20 predictive features, with point position indicating SHAP value magnitude and direction, and colour representing feature value intensity.*

The Level-2B analysis revealed that the model's test accuracy remained relatively unchanged from the Level-1 model, suggesting that energy insecurity had minimal impact on loneliness predictions when controlling for social reliance (being Unable to Turn to Friends and Family). Given the moderately positive relationship shared between food and energy insecurity, the food insecurity feature is likely already capturing / superseding information present in the energy insecurity feature. Examining the feature importance metrics (Figure 5.14) *food insecurity*, *illness*, and *income* still remain the highest contributing features. When comparing the MCR scores for the stigmatised deprivation characteristic *energy insecurity* in Level-2A, the MCR for *food insecurity* is higher than both *illness* and *income*. However, the lower accuracy score of Model-2B compared to Model-2A suggests that *food insecurity* is a more significant predictor of the experience of loneliness than *energy insecurity* in this sample.

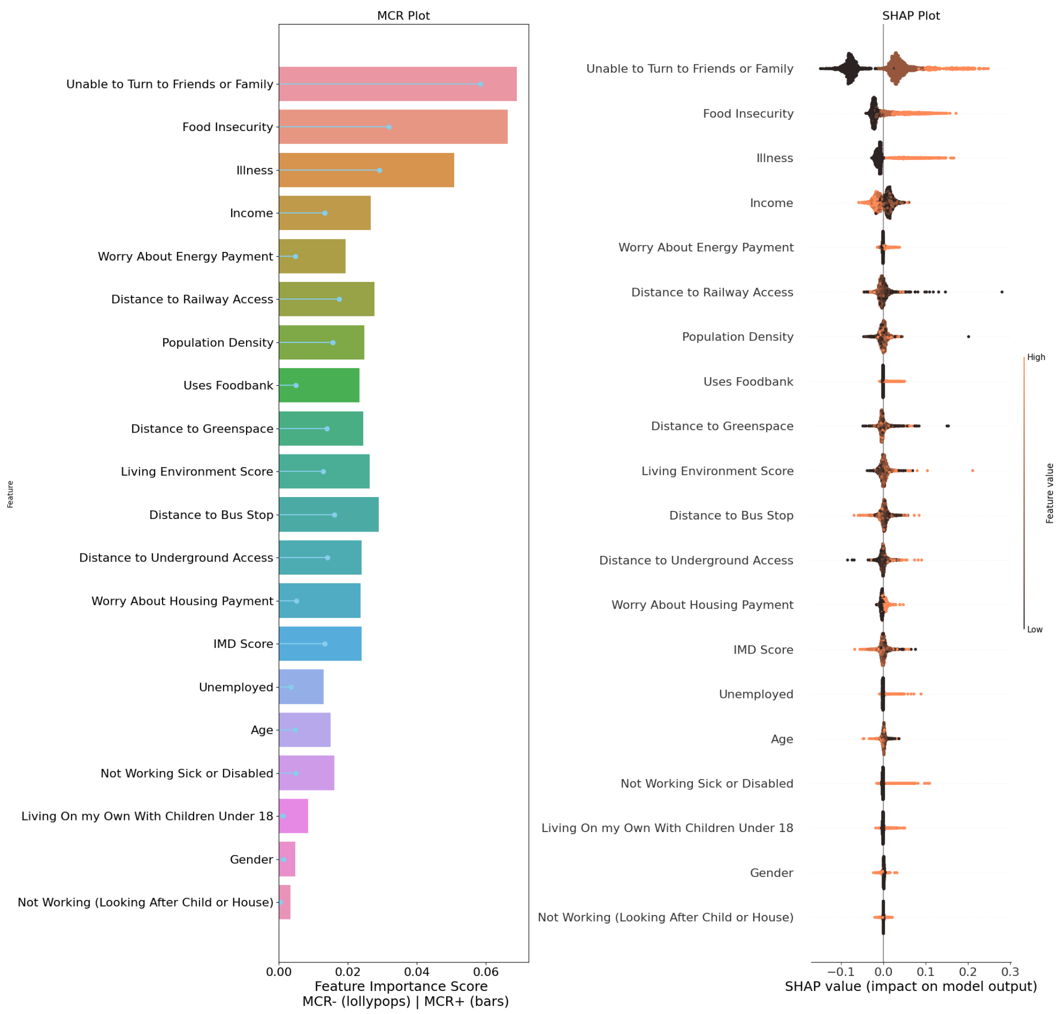

Figure 5.14: *Model-2A (Excluding Energy Insecurity) MCR and SHAP Plots. The left plot displays minimum (**MCR-**) and maximum (**MCR+**) feature values across optimal models. The right plot shows SHAP summary results for the top 20 predictive features, with point position indicating SHAP value magnitude and direction, and colour representing feature value intensity.*

Analysis of Level-3 MCR and SHAP plots (see Figure 5.15) demonstrates that *unable to turn to friends and family* remains the strongest predictor of loneliness, followed by *illness* and *income*. Features representing stigmatised deprivation, particularly *food insecurity*, contribute to the model's ability to capture subtle variations in loneliness predictions. However, the dominant influence of social support availability (measured through the ability to turn to friends and family) emphasises a crucial distinction between social isolation factors and the psychological experience of loneliness itself. Notably, when food and energy insecurity are excluded from the model, 'Illness' shows increased importance, with larger MCR+ and MCR- values compared to Level-2A. This shift suggests that physical and mental health-related challenges may have more direct effects on loneliness when not considered alongside stigmatised deprivation indicators.

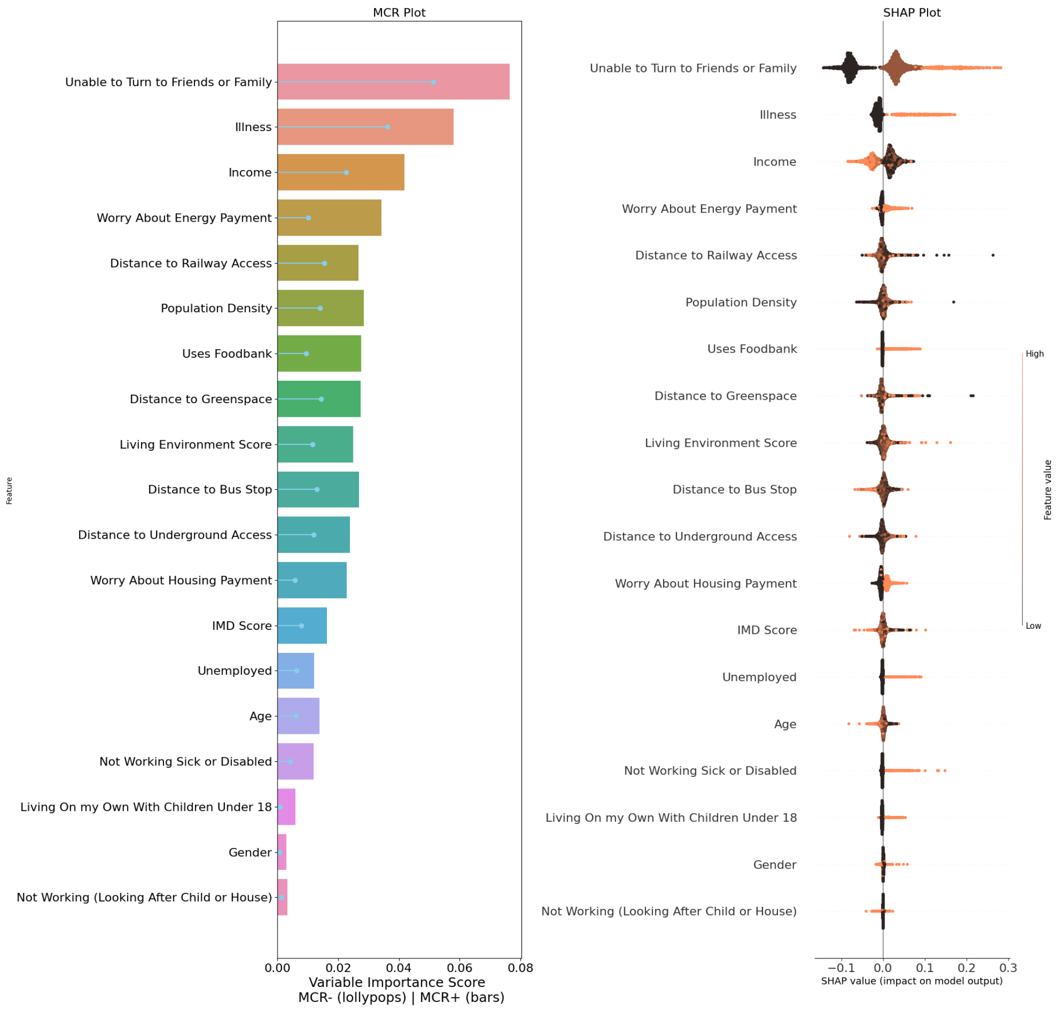

Figure 5.15: *Model C (Excluding Food and Energy Insecurity): MCR and SHAP plots. The left plot displays minimum (**MCR-**) and maximum (**MCR+**) feature values across optimal models. The right plot shows SHAP summary results for the top 20 predictive features, with point position indicating SHAP value magnitude and direction, and colour representing feature value intensity.*

Overall, the model results show that factors that limit autonomy, such as lower income, stress around unaffordable housing or energy costs, and limited access to transport, contribute towards an experience of loneliness. The feature *unable to turn to friends and family* remained consistently at the top of the feature importance plots, suggesting that despite the impact of stigmatised deprivation, having the social support of friends and family is more impactful in the prediction of loneliness. Furthermore, the prevalence of the *illness* feature across all treatments indicates that poor mental or physical health is a consistent predictor of loneliness. Age was a present feature across all model classes (Figure 5.13 Figure 5.14 Figure 5.15), showing that observations with lower ages contributed toward outcomes of loneliness. A more detailed analysis of loneliness and age is warranted to enable further lessons learned, for example through a longitudinal study.

These results offer evidence that experiences of stigmatised deprivation specifically can exacerbate experiences of loneliness. However, the question remains why this is the case of loneliness, and I propose several hypotheses for this, worthy of future attention:

1. **Social Stigma Related to Deprivation and Social Resources**: People experiencing food insecurity may feel ashamed or embarrassed about their situation, leading them to withdraw from social interactions to avoid judgment or scrutiny from others (Leung et al., 2022; Nica-Avram et al., 2021; Pineau et al., 2021; Stack & Meredith, 2018). Food insecurity can cause feelings of shame and stigma, with those who use food banks and other social support mechanisms reporting experiencing feelings of loneliness and social isolation due to the perceived stigma (Pineau et al., 2021; Swales et al., 2020). There is also a consideration for those who live in more affluent areas where food and energy insecurity are less common, who may experience more stigma related to experiencing such deprivation. Food banks operate on a 'deficiency model' that prioritises providing food for the individual person rather than facilitating the chance to eat with others, which in turn would reduce the stigmatised

nature of food insecurity and mitigate against the psychological health impacts of stigmatised deprivation. This is likely exacerbated in areas with fewer social resources, such as food banks, poorer quality social housing, and higher deprivation which contribute towards an increase in loneliness (Kearns et al., 2015).

When evaluating Level-3 in which the stigmatised deprivation features were removed, features including *living environment score* and *IMD Score* align with the literature that shows how governmental support and remedial resources contribute towards feelings of loneliness.

2. **Limited Social Opportunities**: In some cases, individuals facing food insecurity may refrain from participating in social events or gatherings where food is the central focus due to fear of being unable to contribute or partake (Nica-Avram et al., 2021); this idea is also reflected in the ability of individuals to participate in non-food related social events due to limited disposable income(Arenas et al., 2019; Davis et al., 2023; M. Martin et al., 2016; Pourmotabbed et al., 2020). It is also suggested that limited mobility (specifically access to transport) in older people contributes towards feelings of loneliness (Site, Lohan, et al., 2022). This is reflected in the results of each model, where access to various transportation types was a contributing factor, with those further away from transport access points being predicted as lonelier more often, although the directionality of the feature's contribution remains unclear.

3. **Health Impacts**: It is clear that loneliness has an effect on an individual's mental and physical health (Hawkley, 2022; Hawkley & Cacioppo, 2010; Office for National Statistics, 2023). While these results do not necessarily show causality, there is likely a bi-directionality between illness and loneliness, and further research could be done to understand the heterogeneity that may be present within the illness feature.

This study provides further evidence that the experience of loneliness is multifaceted. The features that were determined to be most important across the experiments align with previous studies (Ejlskov et al., 2018; Kearns et al., 2015; Ng et al., 2023). This study builds upon previous work by examining loneliness at a more granular level compared to coarse national studies (Elgar et al., 2021) while also capturing a broader population compared to work that focuses on older adults (Altschul et al., 2021; Ejlskov et al., 2018; Tani et al., 2022). The modelling approach undertaken provides a more nuanced insight into the relationship between loneliness and stigmatised deprivation and health.

5.6 Conclusion

It is clear from the annual reports published by the ONS (Department for Digital, Culture, Media and Sport, 2023; U. K., 2020, 2021, 2022), the Campaign to end loneliness (The Campaign to End Loneliness, 2023) and Public opinions and social trends datasets (Office for National Statistics, 2024) that there is still a steady increase in the percentage of the population that experiences loneliness.

This study's findings demonstrate that stigmatised deprivation, particularly food insecurity, impacts loneliness at an individual level. This not only corroborates previous qualitative research on how stigmatised deprivation affects the experience of loneliness (Burris et al., 2021; S. Park & Berkowitz, 2024; Stack & Meredith, 2018), but emphasises the distinct nature of such challenges versus income deprivation alone. While the predictive power of these forms of deprivation only adds 2.32% accuracy to models of loneliness, this reflects an estimated 200k individuals in the UK who could be better identified as at risk (2.28% of the 9 million people estimated to be lonely either often or all the time in the UK (The Campaign to End Loneliness, 2023)).

However, the relationship between stigmatised deprivation and loneliness may be mitigated through the ability of an individual to socially rely on friends and family, which can be seen consistently across all treatment SHAP and MCR plots.

Stigma-related factors in loneliness modelling significantly affect model accuracy, further confirming the known psychological and social factors surrounding loneliness. However, the feature importance metrics suggest that despite how stigmatised deprivation carries unique psychological and social implications beyond general financial hardship, having a social network one can rely on is more impactful in reducing loneliness. Identifying how social isolation varies with deprivation should thus be the primary focus of policymakers looking to intervene. The challenge of social connection (or lack thereof) could likely be addressed through different initiatives, depending on whether the person is, for example, experiencing food insecurity and therefore lacks the opportunity to eat with other people. Showing a psychological health impact of stigmatised deprivation is the increased experience of emotional loneliness.

Social and environmental features, particularly area deprivation levels and access to green space, emerged as critical moderators of loneliness that moderate the relationship between deprivation and loneliness. Mental and physical illness also appeared as a strong predictor of loneliness across all the defined treatments, providing further evidence for the link between poor health and loneliness.

By examining loneliness across all age groups rather than just older adults, our findings reveal broader patterns in how stigmatised deprivation affects social isolation. By incorporating the spectrum of IMD scores alongside specific measures of stigmatised deprivation, our study offers a crucial context for understanding how various forms of stigmatised deprivation impact loneliness. It is important to note that our sample was limited to London's population. Further exploration is needed into the specific differences between those experiencing mental health concerns versus those with physical illnesses, as this granularity was not present in the dataset analysed.

5.6.1 Limitations and Future Work

Several limitations of this study should be acknowledged. First, the digital data collection approach introduces sampling bias, as Olio requires smartphone access and digital literacy. While the sample is representative of London's IMD distribution, it excludes individuals without smartphone access or the prerequisite digital skills, potentially under-representing certain vulnerable populations.

Second, this study examines the impact of stigmatised deprivation on loneliness rather than direct experiences *of* stigma itself. The focus remains on how specific forms of deprivation (those which carry social stigma) contribute to loneliness, not the psychological processes of stigma perception or its internalisation.

Finally, while this research aims to generate insights beyond specific demographic groups, the findings may have limited generalisability to contexts in which social class and status hierarchies operate differently from those in the UK. Future research should investigate these relationships across diverse cultural and socioeconomic contexts to establish their broader applicability.

Several avenues for future research could strengthen these findings and expand understanding of stigmatised deprivation and loneliness. First, employing more comprehensive loneliness measures, such as the 20-item UCLA Loneliness Scale, would provide greater sensitivity to detect nuanced relationships between deprivation types and loneliness severity.

Future studies should directly measure experienced stigma related to specific deprivation indicators (e.g., food insecurity, receipt of benefits) to establish clearer causal pathways between stigma perception, deprivation experiences, and loneliness outcomes. This would enable more precise examination of the stigma-loneliness relationship proposed in this work. There is a broader challenge which can prevent these insights from being enacted, particularly the public perception of social support mechanisms (such as universal credit and foodbank usage) by the broader society. Why should those who use food banks or require subsistence from the government be shamed out of some minimal comfort. I also raise another question for consideration in future work - what are the broader perceptions of the public's experience of shame when engaging in this food banks or broader social support?

Contextualising this work with more data should be a research priority. Expanding data collection beyond London to include broader UK populations would enhance generalisability. London's unique demographic composition, elevated cost of living, and population density may influence both deprivation patterns and social relationships in ways that differ from other UK regions. Comparative studies across varied geographic and socioeconomic contexts would strengthen the external validity of these findings.

Finally, longitudinal designs could examine how stigmatised deprivation experiences evolve over time and their temporal relationship with loneliness development, providing insights into intervention timing and prevention strategies.

5.7 Concluding Remarks

This study contributes to a comprehensive understanding of loneliness by demonstrating how stigmatised deprivation operates as a distinct pathway to loneliness experiences. These findings build upon practitioner insights from Study 1, which identified stigma as a key barrier preventing clients from directly disclosing loneliness in therapeutic contexts. By quantifying how specific stigmatised deprivations (particularly food and energy insecurity) independently contribute to loneliness, this work provides empirical support for practitioners' observations about the complex ways loneliness manifests.

The identification of these stigmatised pathways has important implications for digital mental health interventions. The findings inform the development of outcome measures (as explored in Study 2) by highlighting which life circumstances may serve as indirect indicators of risk for loneliness. Furthermore, understanding that individuals experiencing stigmatised deprivation may be reluctant to explicitly state they are lonely provides crucial context for Study 4's investigation of latent loneliness self-disclosure detection in text.

Despite ongoing collaborations between UK government departments and charities to reduce loneliness through local initiatives, the Public Opinion and Social Trends data show a steady increase in loneliness across the UK population (from 2020 to 2024). These findings suggest that expanding intervention efforts to include national-level analysis of stigmatised deprivation would enable more effective targeting by better capturing a range of factors which influence loneliness patterns across geographic regions. Such approaches would complement the ability of digital mental health platforms to identify and support individuals experiencing loneliness through indirect disclosure patterns, as examined in the subsequent study of this thesis.

Chapter 6

A Framework for Loneliness Detection in Digital Text and Methodological Critique

Abstract

Background

Natural Language Processing (NLP) has been employed to understand a broad range of mental health experiences and concerns, including schizophrenia, suicide ideation, depression and loneliness. While NLP affords potentially wide-ranging insights into mental health concerns, loneliness research has been predominantly limited to text data generated on social media platforms such as X (previously Twitter) or Reddit. While findings from social media data provide valuable insights into how lonely people disclose and discuss loneliness, these studies face limitations in their data quality and lack of ground truth labels. While traditional NLP approaches can produce outputs that appear to be highly accurate, this is often under-evaluated and, with further investigation, can be shown to be a result of data-confounding. This chapter evaluates the data collection and methodological approach of Jiang et al. (2022) who

reported achieving 98% accuracy across a number of deep learning model architectures.

Objectives

Set against this background, the objectives of this chapter are: 1. To extend prior work by comparing traditional and contemporary ML approaches to identify loneliness self-disclosure in online forums; and 2. Define a novel feature-ablation framework to identify data-confounding issues in social media datasets.

Methods

This chapter is divided into two parts. Part 1 applies traditional and contemporary Large Language Model (LLM) classifiers to the Reddit dataset originally collected by Jiang et al. (2022), aiming to replicate their findings and understand the factors driving their high predictions. The trained models are then applied to a separate dataset from Kooth, a digital mental health platform, to evaluate the model's performance in a related yet previously unseen domain. Part 2 applied a rigorous feature importance (FI) and permutation importance (PI) evaluation, followed by an ablation experiment to conclusively show evidence of data confounding in the Reddit dataset. It then presents a novel framework which enables the detection of data-induced confounding in social media text datasets.

Results

The results of this study show that all the traditional NLP models achieve an accuracy score of >93% in the Reddit dataset, while the LLMs achieve 91%. These results follow the original accuracy results by Jiang et al. (2022) and justify further investigation into potential data confounding, as the model FI suggested the models were learning the signals other than loneliness self-disclosure. Furthermore, as the trained models failed to generalise to forum posts from Kooth, a digital mental health platform, it was found that neither the traditional models nor LLMs were able to generalise to a related text domain. Through the ablation experiment, it was proven that the dataset was causing model confounding and that, rather than detecting loneliness, the model was in fact classifying which Reddit forum the post originated from.

6.1 Introduction

In the preceding chapters, this thesis has discussed how loneliness is a latent and stigmatised experience which people often struggle to express explicitly (chapter 2 and chapter 3). In this chapter, an analysis is undertaken to examine how loneliness is discussed at scale, enabling a more nuanced understanding of loneliness and self-disclosure. Such analysis is useful given the highly time-consuming nature of thematic analysis of therapeutic transcripts or user-generated text (for identifying mental health concerns), which is time-consuming and requires a large amount of specialised domain expertise.

The application of natural language processing (NLP) approaches enables researchers to rapidly and accurately classify text, affording researchers an understanding of how individuals discuss and disclose mental health concerns at scale. With the advent of online forums and digital mental health interventions (DMHI), there is a considerable volume of text data discussing specific mental health concerns. These data could provide researchers with the opportunity to understand the specific language used in disclosing mental health concerns via NLP methodologies applied across clinical and non-clinical settings. The combination of available data of this sort, combined with accurate modelling approaches, enables the development of tools that could provide invaluable insight for practitioners.

The application of NLP for loneliness self-disclosure is challenging. This is due to its subtle, indirect disclosure through linguistic markers of social disconnection, isolation, and relational dissatisfaction rather than direct disclosures. With the increasing volume of text data from online forums and DMHIs, however, there is an opportunity to develop computational approaches that can identify loneliness self-disclosure patterns that practitioners could miss through traditional analysis approaches.

Unfortunately, current approaches to loneliness detection face significant methodological limitations. Existing studies typically rely on keyword matching or unsupervised topic modelling to generalise how loneliness is disclosed online. Moreover, this analysis is particularly timely. Recent advances in NLP, notably attention mechanisms and large language models (LLMs), offer new possibilities for more sophisticated detection approaches (Sun et al., 2024; Xu et al., 2024). However, their application to loneliness remains largely unexplored.

This chapter, therefore, contributes both a methodological framework for detecting loneliness and a critical analysis of existing approaches, ultimately advancing our ability to identify and respond to this pervasive yet often concealed concern.

Part 1 evaluates the efficacy of ML approaches for detecting loneliness self-disclosure by conducting a comparative analysis of traditional NLP approaches and contemporary LLMs for loneliness self-disclosure detection, and develops a methodological framework for the application of LLMs in mental health detection research.

Part 2 conducts a critical analysis of data collection practices in NLP mental health research, through cross-algorithm evaluation; this study shows that bias persists across multiple model architectures, and by employing an feature importance (FI) and ablation analysis, demonstrate that high-performing classification models are learning domain-specific linguistic markers (due to poor data collection practices) rather than loneliness self-disclosure content.

6.2 Background

We are at a turning point in NLP research, with recent developments in text representation, particularly contextualised embeddings and transformer architectures, combined with the emergence of LLMs, have expanded the methodological possibilities for text analysis within NLP research. Contextualised within mental health analysis, NLP has been employed to understand a wide range of experiences and concerns, from predicting satisfaction with life, through the analysis of Facebook message transcripts (Schwartz et al., 2016) or estimating the wellbeing of populations using geo-tagged tweets (Jaidka et al., 2020). Examples of NLP use cases for specific mental health concerns include recognising schizophrenia or suicide ideation from counselling transcripts or detecting depressive symptoms from social media posts (Althoff et al., 2016b; Coppersmith et al., 2018; Oseguera et al., 2017; Strous et al., 2009).

However, while NLP approaches show promise for understanding mental health patterns and concerns, their application is often hindered by data quality issues that can undermine research validity. These concerns are particularly pronounced in loneliness detection research as examined in this chapter.

6.2.1 Identifying the Self-disclosure of Mental Health Concerns Through NLP

Contextualising NLP approaches within mental health interventions, several studies have evaluated therapeutic transcripts to identify recurring themes and model topics (Althoff et al., 2016a; Milligan et al., 2024a; Sridhar et al., 2021). Studies have also focused on the classification of specific mental health concerns (Jackson et al., 2017; Ryu et al., 2021). This work is often focused on depression (Arachchige et al., 2021; Yadav & Sharma, 2023), anxiety (Teferra & Rose, 2023) and suicide ideation (Li et al., 2023; Oseguera et al., 2017) with limited research into loneliness.

Across both social media and therapeutic domains, researchers have predominantly relied on traditional NLP classification such as Support Vector Machines (SVMs), Logistic Regression (LR), and ensemble learning approaches (Badal, Nebeker, et al., 2021), typically employing TF-IDF or n-gram feature representations (Choudhury et al., 2013; Coppersmith et al., 2014; Gkotsis et al., 2017). These approaches typically focus on identifying linguistic markers or self-disclosure patterns associated with mental health concerns rather than the classification of the conditions in the text observations (Chancellor & De Choudhury, 2020).

Statistical approaches, including the Linguistic Inquiry and Word Count (LIWC) framework, have been employed to quantify psychologically relevant word categories, providing insights into emotional, cognitive, and social linguistic patterns within mental health texts (Li et al., 2023; Oseguera et al., 2017). These traditional methods focus primarily on frequency-based representations and surface-level linguistic features, often treating text as collections of independent tokens without considering the contextual or semantic relationships across documents.

The emergence of contemporary large language models (LLMs) and advanced word embedding techniques has expanded the potential for the accurate detection of mental health concerns (Sun et al., 2024). Embedding methods such as Word2Vec, GloVe, and transformer-based models like DistilBERT can be adapted to generate domain-specific representations of language use in mental health contexts. When integrated with deep learning architectures, these embeddings can enhance the performance of text analysis tasks, including classification, sentiment detection, and topic modelling (Asudani et al., 2023).

However, concerns have been raised throughout the literature regarding the ethical implications and interpretability of LLMs (Guo et al., 2024; Ji et al., 2023; Pandey, 2024). This lack of explainability is compounded by challenges related to data availability and quality across the mental health domain, and the nuanced nature of mental states (Hua et al., 2025). To mitigate against these data limitations, researchers have increasingly engaged with online-generated text data, following traditional NLP research approaches for identifying self-disclosure of specific mental health concerns (Lawrence et al., 2024; Xu et al., 2024). Despite these challenges, there is a growing body of research applying LLMs to detect specific mental health concerns, such as stress (Xu et al., 2024) or suicide ideation (Xu et al., 2024), while loneliness remains underexplored.

6.2.2 NLP Approaches for Loneliness Self-disclosure Detection

Current approaches to detecting loneliness in online text data have faced a common issue: researchers have been restricted to identifying loneliness through *explicit disclosures*. (Yet, the nature of loneliness itself means that indirect expressions are often missed during data collection if the text does not explicitly contain a word such as "Lonely" or "Isolated"). This issue emerges because loneliness is stigmatised, which discourages explicit self-disclosure. Research on loneliness and self-disclosure has been predominantly limited to text data generated on social media platforms such as X (previously Twitter) or Reddit (Andy, 2021; Guntuku et al., 2019; Koh & Liew, 2022; Ng et al., 2023). This reliance on social media data is undoubtedly due to the limited access to sensitive therapeutic transcript data. While findings from social media analysis provide valuable insights into how individuals engage in online discussions around loneliness and its lived experience, studies based on social media data face two significant limitations:

1. They lack the contextual depth and psychological framing available in therapeutic settings, as the data is not directly related to clinical environments.

2. They typically identify loneliness through explicit keywords ("Loneliness", "Lonely", "Isolated") rather than capturing the subtle ways in which loneliness is indirectly expressed. Studies by Kiritchenko et al. (2020)

and Guntuku et al. (2019) rely on data collection methods that capture only direct self-disclosure of loneliness, missing linguistic patterns and contextual cues that signal loneliness indirectly.

These limitations align with Chancellor and De Choudhury (2020) broader critique of mental health research in computational social science, in which they identified "concerning" trends regarding construct validity and methodological rigour in how researchers operationalise and identify mental health conditions. Primarily, the language features used in data collection approaches and the limited capture of demographic information, in combination, restrict the understanding of how loneliness manifests across different populations and contexts.

The predominant data collection approach of scraping online posts containing loneliness-related keywords raises potential validity concerns, depending on the research objective. Studies such as Guntuku et al. (2019) and Kivran-Swaine et al. (2014) scrape posts containing terms such as "loneliness" or "solitude"; however, the presence of these keywords does not automatically indicate that the poster is disclosing a personal experience of loneliness. For example, users may express support ("You are not alone") or quote literature, rather than revealing personal struggles. Guntuku et al. (2019) identifies common limitations, such as the study sample, which consists of social media data, and that these data are often not representative of the general population. They further acknowledge that some posts mentioning loneliness may have been metaphorical or non-sequiturs.

Due to the absence of ground-truth labels, these studies typically employ unsupervised approaches to extract insights from the text, thereby limiting their ability to develop robust classification models. The exceptions to this lack of labelled loneliness data are two Reddit datasets by W. Fan et al. (2025) and Jiang et al. (2022); However these studies highlight a limitation across the research domain in which datasets are either unlabelled, or the research is published but without either the dataset ((W. Fan et al., 2025)) *or* the code to validate and replicate the results ((Jiang et al., 2022)).

6.2.3 The Challenges Associated with Labelling Loneliness Self-disclosure

Jiang et al. (2022) explains that annotated datasets, rather than just keyword-based data scraping, can prevent prediction bias for keywords when training text classifiers, further suggesting that labelled data enables the capture of a broader range of loneliness expressions. However, labelling a scraped dataset requires meticulous frameworks or taxonomies to enable the labels to closely align with the observed text and the construct of loneliness. Loneliness measures enable the development of a granular conceptualisation of the concern, particularly longer form scales such as the 20-item UCLA Scale or the 11-item De Jong Gierveld Loneliness Scale (de Jong-Gierveld, 1987; D. W. Russell, 1996). Each scale affords slightly different insights into loneliness that are crucial to consider in tandem when evaluating the self-disclosure of loneliness.Garg et al. (2023) produced a labelled dataset of Reddit posts based on whether their content matched the overarching themes of three prominent loneliness measurements (The UCLA and DGJ Loneliness Scales). This conceptual consideration is critical because the contexts in which loneliness can be expressed online are unstructured, allowing for a wider array of contexts in which loneliness can be disclosed, unlike the more limited contexts captured by traditional measures of loneliness, such as the 4-item UCLA scale.

While loneliness measurement items can be used to understand an individual's experience of loneliness, this *does not directly translate* to a tool for labelling loneliness concerns in text data. There are granular approaches to labelling loneliness self-disclose within text data, particularly Kivran-Swaine et al. (2014)'s framework (See Figure 6.1), identifying how loneliness is disclosed in online contexts: 1. temporal bounding, 2. context of the loneliness (social,

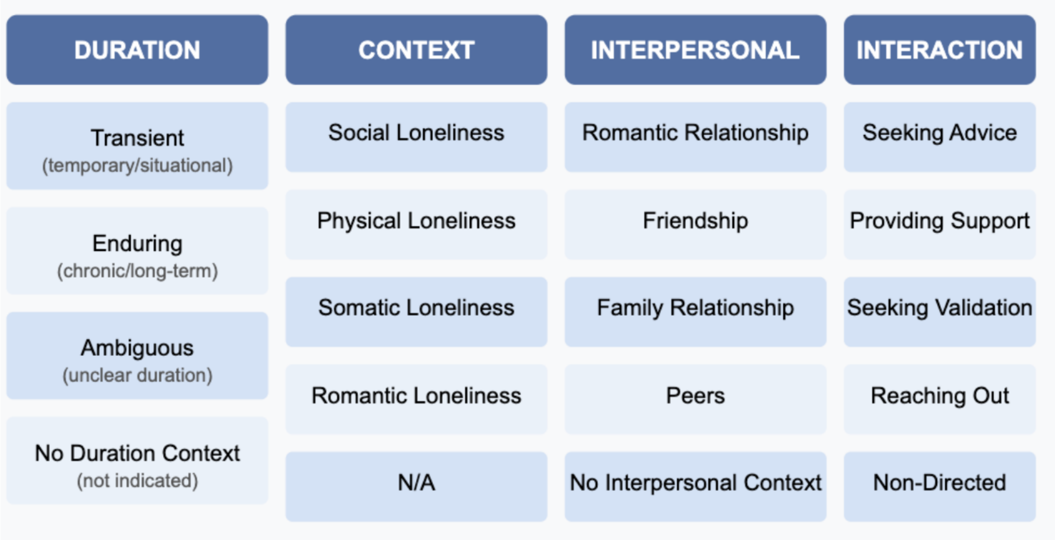

Figure 6.1: *Granular Loneliness Labelling Taxonomy by Kivran-Swaine et al. (2014)*

physical, romantic), 3. explicit interactivity within the expression (Seeking Advice, Providing Support, Reaching out). The categorisation of loneliness was expanded upon by (Jiang et al., 2022), which added a fourth dimension to describe whether the loneliness expression was related to a specific interpersonal relationship (friendship, romantic, or family). However, there are some limitations in this framework that can refine its clarity when used as a labelling guide. Specifically, the presence of overlapping concepts across the *Interpersonal* dimension raises the question of how to define the difference between friendship and peers, given that these interpersonal contexts can often overlap.

Given these methodological concerns around data quality, construct validity, and study replication, claims of exceptionally high accuracy (>98% in loneliness classification tasks by Jiang et al. (2022)) warrant scrutiny. Are models truly that good at detecting loneliness in free text? The reported success across multiple model architectures raises questions about whether such performance reflects considerable advances in loneliness self-disclosure detection, or whether this is potentially an example of poor data collection practices and result analysis.

6.3 Study Aims

Set against this background, the objectives of this exploratory study are: 1. To extend prior work by comparing traditional and contemporary ML approaches to identify loneliness self-disclosure in online forums; 2. Evaluate the trained model's ability to transfer this insight across domains to a related dataset from a different domain; 3. Define a novel feature-ablation framework to identify potential data-confounding issues in social media datasets; and 4. Suggest a data collection framework to prevent future data-confounding in the NLP mental health research

6.4 Methodology

Part 1: Predicting Loneliness in Forum Posts

6.4.1 Data Sample and Procedure

The primary dataset used in this chapter is a Reddit dataset collected by Jiang et al., (2022)(Jiang et al., 2022) concerning labelled loneliness self-disclosure. A secondary forum dataset from the DMHI Kooth was used to evaluate the trained models ability to generalise to a related dataset. The Reddit dataset was selected due to the comprehensive granular labelling taxonomy applied to the dataset and the high reported predictive performance. The Reddit dataset was also an example of a labelled dataset identifying disclosures of loneliness, which is uncommon across the literature.

Reddit Dataset Descriptive Statistics

The ground truth dataset contained a total of (n = 5,633) observations with 3000 non-lonely and 2633 lonely (See Table 6.2 and Figure 6.2 for a breakdown of the distributions across the dataset initially collected by Jiang et al.,(2022)). This dataset was scraped from 4 Reddit subreddits as described

Table 6.1: Age Demographics of Annotated Lonely Posts by Subreddit

Subreddit Group	Posts with Age Labels (%)	Under 18 (%)
r/youngadults & r/college	28.6	16.7
r/lonely & r/loneliness	24.5	24.9

Age demographic percentages are calculated only for posts containing age information. The second column shows what proportion of lonely posts in each subreddit group contained age labels.

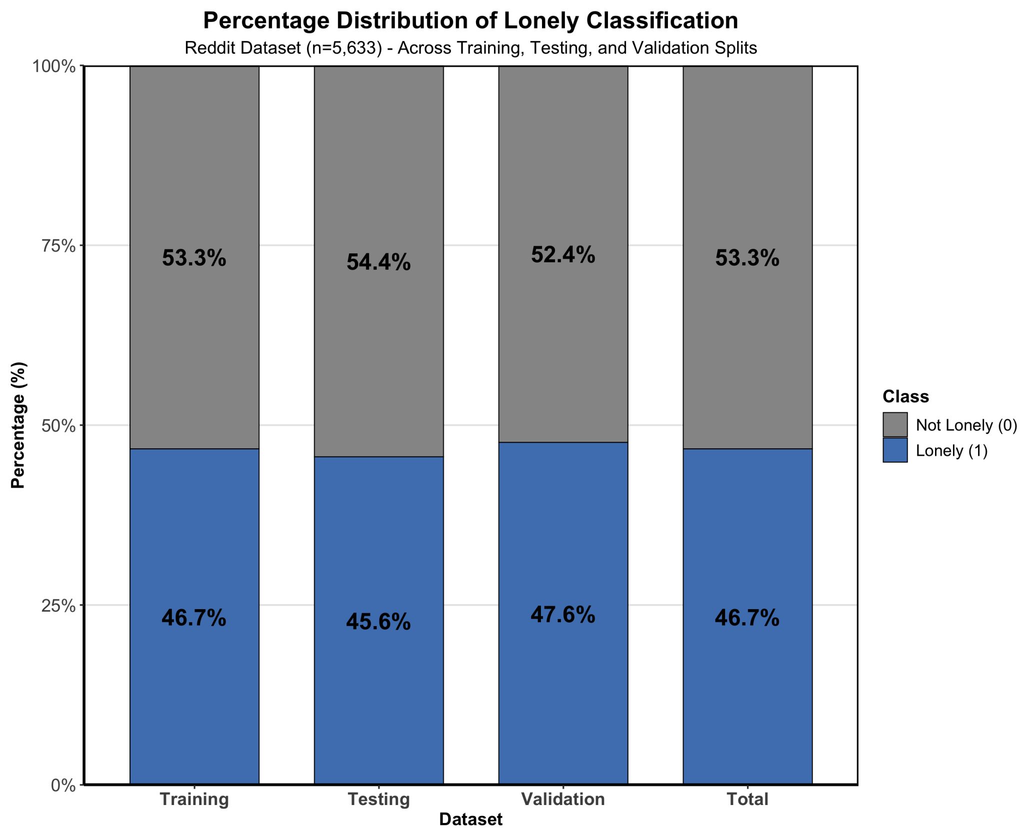

Figure 6.2: *Distribution of lonely class labels of the Jiang et al.,(2022) Reddit dataset*

in Table 6.1. This dataset was collected by scraping Reddit posts using Reddit's Pushshift API. Four subreddits were scraped: r/youngadults, r/college, r/lonely, r/loneliness. To ensure the posts contained meaningful content for annotation, the original authors only considered posts with at least 25 words in the post title and body combined. The data was then labeled by Mechanical Turk workers (MTurkers). Mechanical Turk is a platform where researchers can pay for freelance labelers to label data. Six research assistants also participated in labeling, but it is unclear which posts were labeled by MTurkers or research assistants.

Table 6.2: Summary Statistics for Ground Truth Dataset

Dataset	Not Lonely	Lonely	Not Lonely (%)	Lonely (%)
Training	2,103	1,840	53.3	46.7
Testing	307	257	54.4	45.6
Validation	590	536	52.4	47.6
Total	3,000	2,633	53.3	46.7

Note: Class ratio (Not Lonely:Lonely) is 1.14:1

6.4.2 Machine Learning Methodology

Two NLP classification strategies were applied to the Reddit dataset. The first applied a suite of traditional ML classification models, with a comprehensive grid search where applicable. The second approach evaluated DeepSeek LLMs (DeepSeek-AI et al., 2025) (both base and fine-tuned versions), using a detailed prompt to classify the Reddit posts and extract the granular elements of lonely posts according to the predefined taxonomy from Jiang et al. (2022). The goal of the LLM-based approach was to assess its efficacy in two tasks: 1. classifying posts according to a binary loneliness categorisation, and 2. extracting fine-grained elements of loneliness in the lonely posts. To ensure consistency and comparability, the same dataset splits were applied across both the LLM and the traditional approaches.

LLM Modelling Framework for Loneliness Self-Disclosure Detection

Base and fine-tuned LLM classification was implemented to evaluate the efficacy of base and domain fine-tuned LLMs for loneliness self-disclosure classification. A base Deepseek model was prompted using a zero-shot learning approach, where an LLM is given a task without prior training or examples. This is followed by a fine-tuned model, a set of training examples with "prompt-completion" pairs (examples of correct LLM model outputs given the specific prompt), which present the model with an example forum post, the outcome classification and desired output structure. This domain fine-tuning was implemented to improve both the accuracy of the model classifications and the

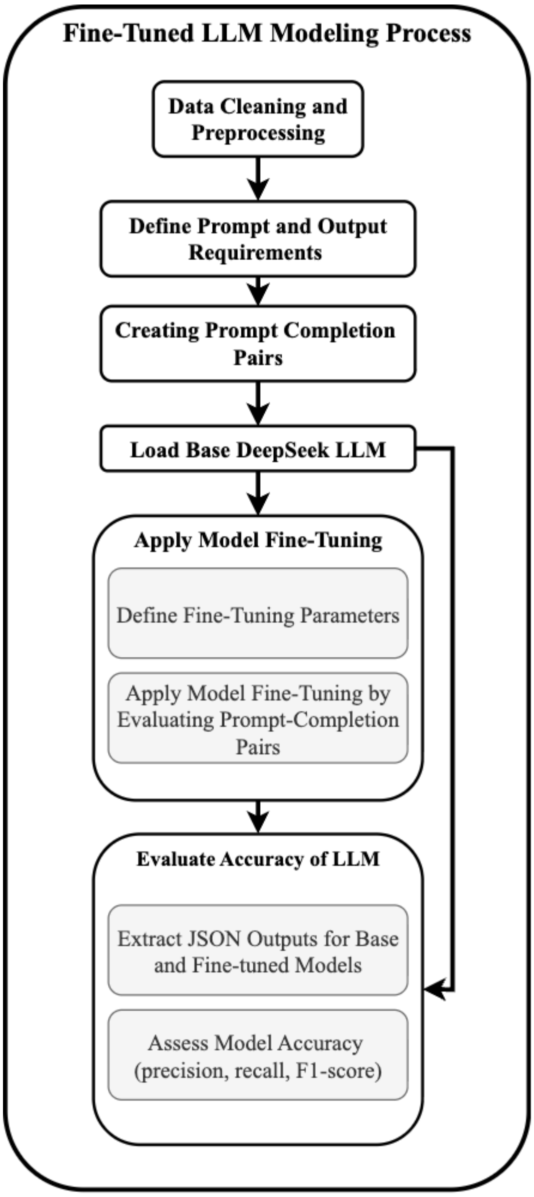

Figure 6.3: *LLM Modelling Process Framework*

consistency of the outputs. Given the sparsity of the taxonomy elements presented in the dataset, this approach enables the evaluation of LLMs' ability to detect the nuances of loneliness self-disclosure identified in the taxonomy with limited fine-tuning examples.

Prompt Design and Implementation

The prompt framework employed is comprised of three primary components: 1. system-level prompts that define the LLM's role and output constraints, 2. user-level prompt that provides the text to be analysed alongside the cate-

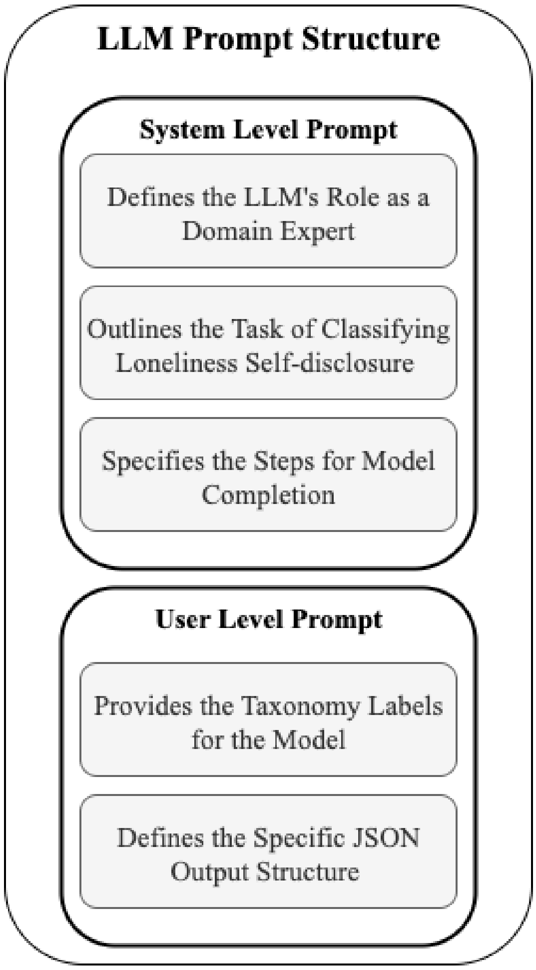

Figure 6.4: *LLM Prompt Design*

gorical loneliness definitions, and 3. a standardised JSON output schema that describes the desired structured responses. The framework integrates the established loneliness taxonomy dimensions in Figure 6.1, enabling systematic classification while preserving the nuanced understanding required for mental health applications.

System-Level Prompt

The system prompt establishes the input framework and output constraints for the LLM to enable more consistent analytical behaviour by defining the expert role and enforcing structured output requirements that prevent deviation from the specified classification task. The system prompt included the requirement for JSON-only responses to mitigate against the variability in output structure. The role definition positions the model as a "domain expert", while the operational rules ensure adherence to the specified framework without extraneous commentary or interpretation beyond the required structured output. The complete prompt is shown in Appendix C.

User-Level Prompt and Taxonomy Integration

The user instruction component integrates the elements of the loneliness taxonomy in Figure 6.1 with the classification requirements lonely or not-lonely. The prompt provides the target text for analysis, followed by comprehensive category definitions derived from the loneliness taxonomy.

JSON Output Schema Requirements

The structured output format requires binary classification of loneliness self-disclosure, accompanied by explanatory reasoning and categorical assignments when loneliness is detected. The schema defines a specific reasoning component that explains the loneliness determination alongside specific textual indicators (*or lack of*).

Category assignments are provided only when loneliness is present, with null values assigned otherwise. This approach ensures that categorical classifications remain meaningful and directly related to identified loneliness expressions rather than forcing inappropriate categorisation of non-lonely content.

LLM Fine-tuning Process

Low-Rank Adaptation (LoRA) was selected as the fine-tuning approach to enable task-specific model adaptation to the domain of mental health classification. LoRA allows fine-tuning of LLMs with minimal computation overhead and reduced memory requirements compared to full parameter fine-tuning. LoRA fine-tuning was conducted using the Unsloth framework (Han & Han, 2023) for optimised memory management and training efficiency (See Appendix D for the complete LoRA fine-tuning parameters).

Traditional Modelling Approach

Bag-of-Words models with TF-IDF vectorisation were selected due to the interpretability they afford, when validating that the models have learned meaningful loneliness indicators rather than exploiting learning shortcuts. Unlike deep learning approaches that can achieve suspiciously high performance without tools to understand prediction drivers, traditional models allow direct examination of which linguistic features drive predictions through SHAP values and permutation feature importance analysis. Four supervised learning algorithm classes were evaluated (Visualised in Figure 6.5): Logistic Regression (LR), Support Vector Machine (SVM), Random Forest (RF), and Extreme Gradient Boosting (XGBoost). Each algorithm was implemented using scikit-learn with a preprocessing pipeline for data cleaning and TF-IDF vectorisation.

Each model class was implemented twice, first with the model's default configuration to establish baseline performance, and an exhaustive grid search optimisation across algorithm-specific hyper-parameter spaces to maximise model performance.

All model classes were evaluated using stratified train-validation-test splits to ensure robust performance assessment. The majority class baseline provided a lower-bound performance reference for comparison. Model performance was assessed using accuracy, precision, recall, F1-score, and Area Under the ROC Curve (AUC) across all data splits (Training, Testing and Validation) to evaluate both predictive performance and generalisation.

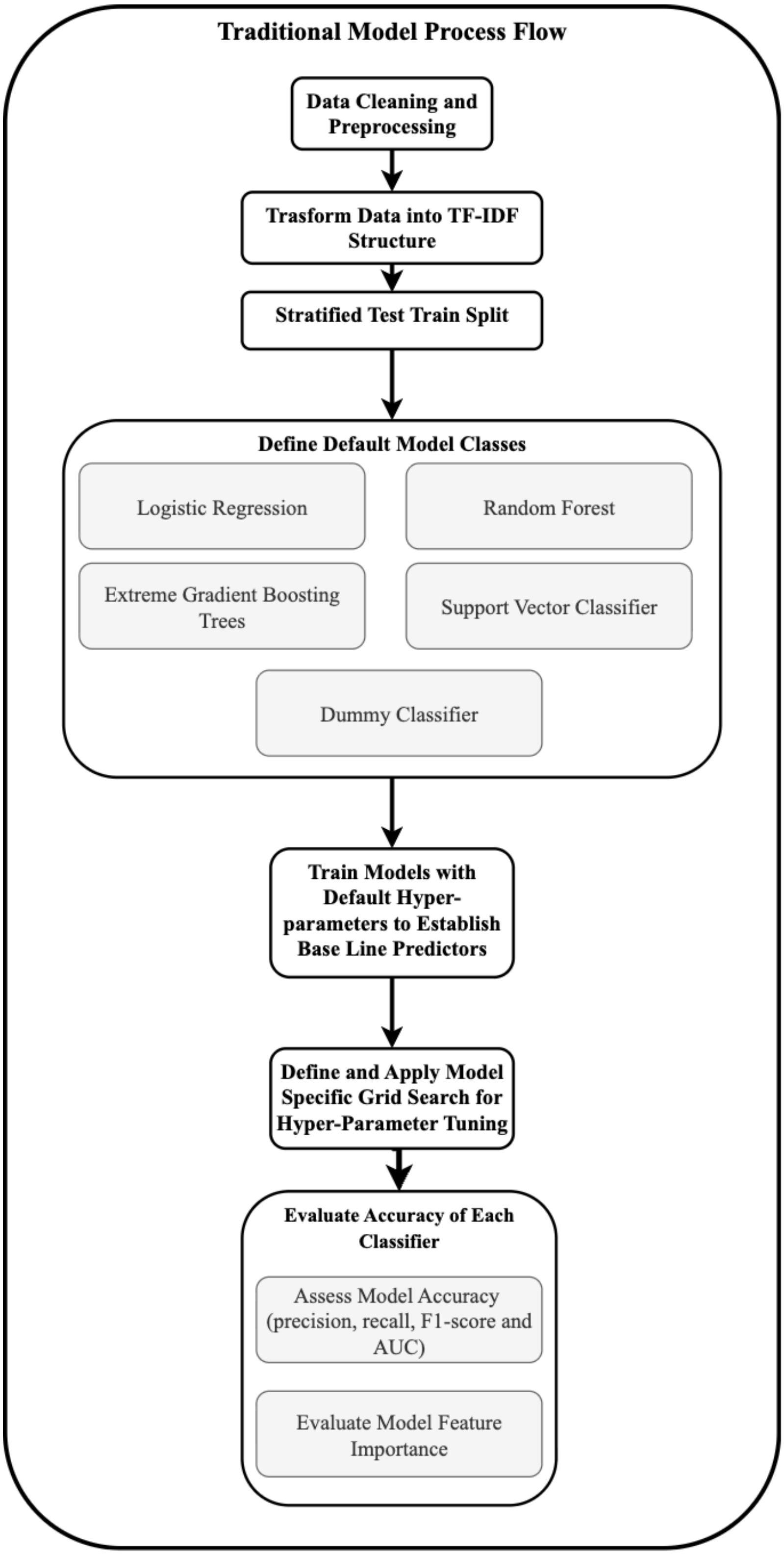

Figure 6.5: *Traditional Model Process Flow Diagram*

6.4.3 Text Representation Approach

The Term Frequency Inverse Document Frequency (TF-IDF) approach to data representation was selected for the traditional model implementations due to the interpretability and explainablity of the TF-IDF scores compared with deep-learning embedding methods (such as Word2Vec or BERT Embeddings). TF-IDF converts text into numerical features by weighting words based on their frequency within documents (TF) and rarity across the corpus (IDF). This creates a representation where words that are both locally important (within a single post) and globally distinctive (across all posts) receive higher scores across a corpus. This approach to representing data for ML models addresses the notion that if someone uses the word "lonely" multiple times in a single post, that word is probably central to what they are trying to communicate. The IDF component captures how distinctive a word is across the entire collection of documents. Words that appear in every document receive low IDF scores because they do not help distinguish one document from another. Conversely, words that appear in only a few documents receive high IDF scores because they are more discriminative.

Data Cleaning Approach

The data cleaning processes were defined as part of a preprocessing pipeline in the following steps: 1. Posts were converted to lowercase and stripped of white space; 2. URLs were replaced with the placeholder token [URL] rather than removed entirely, preserving the semantic information; 3. Escaped characters (e.g., '\n', '\t') and special punctuation were removed (using regular expression patterns), followed by white space normalisation; 4. Each post was tokenised using NLTK's word tokeniser, segmenting posts into individual word tokens; 5. Selective stopword removal was undertaken by removing standard English stopwords except for loneliness-relevant terms (alone, lonely, isolated, nobody, no one), which were preserved as they carry critical semantic meaning for the classification task; 6. Tokens were lemmatised using WordNet's lemmatiser combined with POS tagging to ensure accurate root form extraction.

6.4.4 Code Availability

The complete code for the data preprocessing, machine learning models, and analysis presented in this chapter is available at: https://github.com/GregorMilliganUoN/Chapter6_A-Framework-for-Loneliness-Detection-in-Digital-Text-and-Methodological-Critique.

6.5 Experimental Results

This section covers the LLM and traditional modelling results, showing the accuracy of the models and the feature importance of the traditional models. Table 6.3 presents the LLM performance across both base and fine-tuned DeepSeek models (with Table 6.4 showing the LLMs performance in detecting the granular taxonomy of loneliness), while Table 6.6 shows the complete set of traditional model results.

6.5.1 LLM Model Results

Fine-tuning the LLM improved both output consistency and model classification performance. The fine-tuned JSON model achieved an accuracy of 91% and 90% for the validation and test datasets respectively, while the base JSON model did not produce enough consistent JSON outputs to enable model evaluations. Notably, when evaluating only successfully parsed outputs (excluding system errors), all models achieved consistent performance (89-90% accuracy), indicating that parsing failures rather than classification errors were the primary limitation of this LLM implementation. It should be noted that these results must be contextualised against the significant parsing challenges that limited the scope of evaluation. Despite specific prompting instructions, system errors remained present across all configurations, highlighting the practical challenges of implementing LLMs for structured classification tasks in real-world applications.

Table 6.3: Performance Evaluation of DeepSeek Language Models for Loneliness Classification (JSON Format)

Performance Metric	Base Model		Fine-tuned Model	
	Validation	**Test**	**Validation**	**Test**
Total Samples	1,126	564	1,126	564
Parse Success Count	109	132	1,057	529
Parsing Success Rate	9.7%	23.4%	93.9%	93.8%
Accuracy†	Performance not evaluable		0.91	0.90
F1-Score†	Performance not evaluable		0.91	0.89

†Performance metrics calculated only on successfully parsed cases where sample size permits reliable evaluation.
Note: Base model parsing success rates below 25% preclude meaningful performance evaluation. Fine-tuning demonstrates essential improvement in both parsing reliability and classification capability.

Table 6.4: Fine-grained Loneliness Classification Fine-tuned Deep Seek Model Performance

Dimension	**Fine-tuned Model (%)**
Context	0.464
Duration	0.317
Interpersonal	0.250
Interaction	0.237

Contrastingly, the LLM did not perform well on the granular elements of the loneliness disclosure; even when fine-tuned, the results were poor (See Table 6.4). This performance is likely due to the imbalance in granular elements of the taxonomy, meaning the model would be unable to consistently detect this granular loneliness element signal even when fine-tuned, due to the minimal number of examples in the dataset. This is unlike the results achieved by (Jiang et al., 2022) (shown in Table 6.5), which show accuracies of 86%, 84%, and 79% for the contextual, interaction and interpersonal elements of the loneliness disclosure, respectively.

Table 6.5: Accuracy Results for Distributional Fine-grained Loneliness Classification from Jing et al. (2022).

	Accuracy
Duration	
LSTM Baseline	0.4059 ± 0.0018
BERT + MLP	$\mathbf{0.5992 \pm 0.0114}$
HDLN	0.4539 ± 0.0073
Context	
LSTM Baseline	0.7198 ± 0.0000
BERT + MLP	$\mathbf{0.8573 \pm 0.0102}$
HDLN	0.8560 ± 0.0220
Interpersonal	
LSTM Baseline	0.5758 ± 0.0000
BERT + MLP	$\mathbf{0.7976 \pm 0.0031}$
HDLN	0.7795 ± 0.0191
Interaction	
LSTM Baseline	0.6459 ± 0.0000
BERT + MLP	$\mathbf{0.8352 \pm 0.0120}$
HDLN	0.7237 ± 0.0138

6.5.2 Traditional Model Results

The traditional modelling performance is shown in Table 6.6, two models of each model class were implemented to assess the impact of increasing parameter complexity across model classes. It is clear from the high accuracy scores (all models achieving >90% accuracy) that there is a form of procedural overfitting occurring. A comparison of the base model and grid-searched models is shown in Figure 6.6 and Figure 6.7. A rigorous review of the data preprocessing, splitting and modelling approach was undertaken to ensure there was no data leakage. The high accuracy across all model classes also aligns with the results presented in the original paper by Jiang et al. (2022), as identified in Table 6.12.

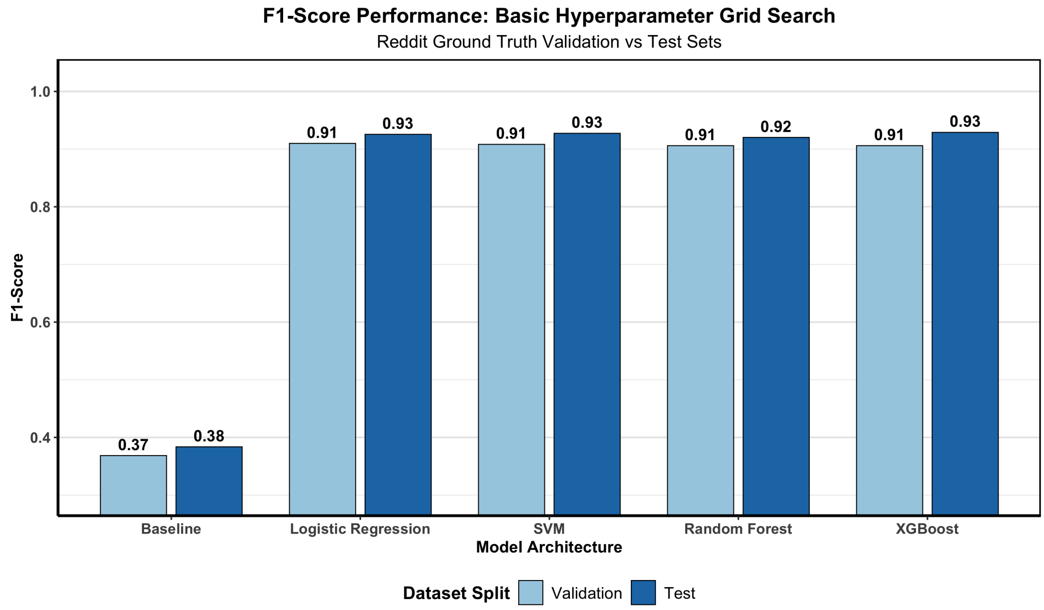

Figure 6.6: *F1-score performance comparison of traditional classification models using basic hyper-parameter configurations. All models demonstrate substantial improvement over the baseline, with consistent accuracy scores.*

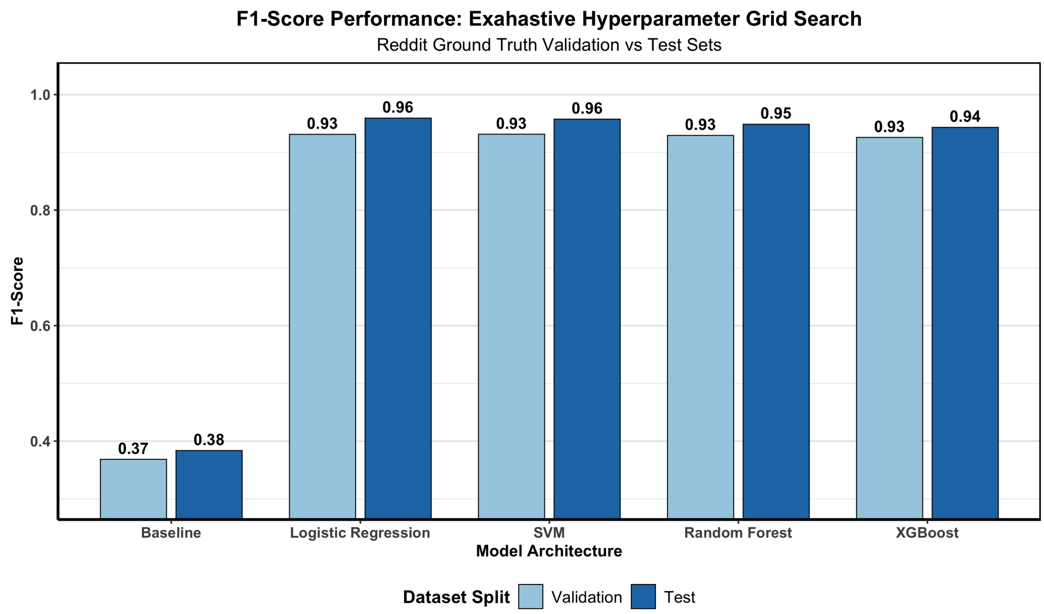

Figure 6.7: *F1-score performance comparison of traditional classification models using exhaustive hyper-parameter configurations. All models demonstrate substantial improvement over the base models, with consistent accuracy scores.*

Table 6.6: Performance Summary of Traditional Based Text Classification Models

Model	Parameters	Test Set			Validation Set			Training Set		
		Acc	F1	AUC	Acc	F1	AUC	Acc	F1	AUC
Baseline	most_frequent	0.54	0.38	0.50	0.53	0.37	0.50	0.53	0.37	0.50
LR Base	C=1.0, max_feat=100, (1,1)	0.93	0.93	0.98	0.91	0.91	0.97	0.92	0.92	0.97
LR Exhaustive	C=10.0, max_feat=1500, (1,2)	**0.96**	**0.96**	**0.99**	**0.93**	**0.93**	**0.98**	0.99	0.99	**1.00**
SVM Base	C=1.0, max_feat=100, (1,1)	0.93	0.93	0.98	0.91	0.91	0.97	0.92	0.92	0.97
SVM Exhaustive	C=1.0, linear, max_feat=1500, (1,2)	**0.96**	**0.96**	**1.00**	**0.93**	**0.93**	**0.98**	0.97	0.97	**1.00**
RF Base	depth=10, n_est=100, max_feat=100	0.92	0.92	0.97	0.91	0.91	0.97	0.95	0.95	0.99
RF Exhaustive	depth=None, n_est=200, max_feat=1500	0.95	0.95	0.99	**0.93**	**0.93**	**0.98**	**1.00**	**1.00**	**1.00**
XGB Base	lr=0.1, depth=3, n_est=100	0.93	0.93	0.98	0.91	0.91	0.97	0.94	0.94	0.98
XGB Exhaustive	lr=0.1, depth=6, n_est=100	0.94	0.94	0.98	**0.93**	**0.93**	**0.98**	0.98	0.98	**1.00**

Note: Performance metrics shown are Accuracy (Acc), F1-score (F1), and Area Under ROC Curve (AUC) evaluated across test, validation, and training sets. The Parameters column indicates the number of trainable parameters. **Bold values** represent the highest performance achieved for each metric. The complete table of results can be found in Appendix E Table E.1.

6.5.3 Evaluating Loneliness Prediction Drivers

To understand what is driving this high model performance, a FI analysis was undertaken. FI quantifies each feature's contribution to an ML model's predictive performance, with higher values indicating greater importance in determining the outcome. This experimental methodology enables an initial understanding of the ML prediction output, which is particularly pertinent for this analysis, given the high predictive performance of all model classes and the lack of reported investigation offered by Jiang et al. (2022).

Traditional Feature Importance Examination

Reviewing the SVM FI plot (Figure 6.8), some expected features present with high importance signifying direct loneliness disclosure identified in the broader literature including keywords such as: "lonely", "alone", "loneliness" with other examples such as "friend", "someone" and "talk" showing that words related to friendship and communication with others as highly predictive of loneliness. However, Figure 6.8 only shows the absolute coefficient values across the feature importance scores; crucially, it does not show which class the feature is predicting towards (i.e. if the feature contributes towards the prediction outcome lonely or not-lonely). This can lead to a misinterpretation of the model drivers, where one might misconstrue the high model performance as stemming from features that align with insights from the broader research literature on loneliness, particularly in terms of language related to direct loneliness disclosure (Badal, Graham, et al., 2021).

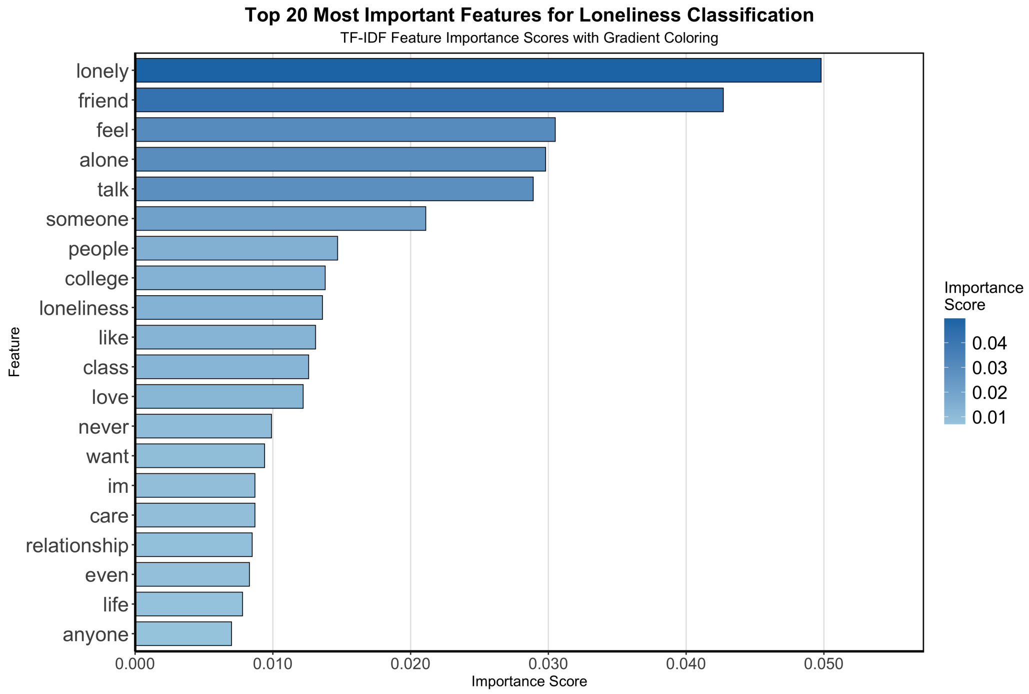

Figure 6.8: *To 20 Features for loneliness binary classification based on traditional feature importance scores (SVM Model). The horizontal bar chart displays features ranked by their contribution to model performance.*

6.6 Evaluating the Model's Ability to Generalise

To test whether the trained models (traditional and LLM) had learned patterns of loneliness expression rather than keyword associations, the highest-performing classifier was applied to posts from Kooth's mental health forum, a therapeutic intervention platform distinct from Reddit. This cross-domain application provides a test of model generalisability: if the models had only learned Reddit-specific linguistic markers, performance should deteriorate when encountering loneliness expressions in a therapeutic forum context, or incorrectly label posts about other mental health issues as expressing loneliness. However, the Kooth dataset lacks ground truth labels for loneliness classification, necessitating a qualitative rather than quantitative evaluation approach. Despite this limitation, sustained accurate performance would suggest the models captured more fundamental patterns of how loneliness manifests in online written communication.

6.6.1 Kooth Dataset Descriptive Statistics

The Kooth forum dataset consisted of posts (n = 140,027) from Kooth Service users (SUs) (n = 22,631). On the Kooth platform, SUs are labelled with 'Presenting Issues' (See Table 6.7), discrete categories of mental health concerns elicited either through one-on-one text-based therapeutic sessions or via forum posts moderation. The Kooth dataset also provided demographic features such as Gender (See Table 6.8)and Age. It should be noted that there is a significant proportion of the sample in the

Table 6.7: Top Presenting Issues among Kooth Users

Prevalence	Presenting Issue	Count
1	No presenting issues	9,079
2	Anxiety/Stress	6,408
3	Family Relationships	3,632
4	Friendships	3,515
5	Self Harm	3,281
6	School/College issues	2,879
⋮	⋮	⋮
16	Loneliness	1,193

Table 6.8: Kooth Forum Data Gender Distribution

Gender	Count
Female	15,194
Male	4,536
Gender Fluid	801
Nonbinary	735
Agender	482
Other Self-Disclosed	362

6.6.2 Applying the SVM to Kooth Forum Data

The results expose fundamental data confounds that prevent the model from generalising beyond the original training context, while simultaneously revealing the limitations of keyword-based approaches in handling contextual nuance.

When applied to the Kooth dataset, the highest-performing SVM systematically failed to distinguish between loneliness self-disclosure and supportive communication, despite both containing identical loneliness-related keywords. Of the top 20 posts with the highest prediction probabilities for loneliness, 13 (65%) were supportive messages rather than expressions of loneliness, all of which received maximum prediction probability scores (the model's confidence in the post expressing loneliness) of 1.00. This consistent misclassification demonstrates that the model learned superficial keyword associations rather than meaningful patterns of loneliness expression, confirming both the presence of data confounding and an inherent limitation of keyword-based methods in identifying loneliness self-disclosure, which compromises cross-domain validity.

6.6.3 Applying the Fine-tuned LLM to Kooth Forum Data

The LLM outperformed traditional approaches in addressing these systematic failures. Applied to the same 20 posts that the SVM misclassified with maximum confidence, the model correctly identified 17 as "not lonely", with only 1 incorrect classification and 2 unparseable outputs (A sample is shown in Table 6.10 and the set of 20 observations is provided in Appendix F). This represents a substantial improvement over the SVM's inability to distinguish between expressions of loneliness and supportive communication.

The model also provides explicit reasoning for its classifications, offering interpretability that traditional approaches lack. These explanations reveal that the model focuses on explicit language related to loneliness and emotional distress indicators, although it still struggles with the contextual nuance required to distinguish between discussing loneliness and experiencing it. Nevertheless, this approach demonstrates clear advantages in cross-domain applications, suggesting that while fundamental data confounding issues persist, the model can better navigate the contextual complexities that undermined keyword-based methods. A sample of the LLMs classification and reasoning is demonstrated

Table 6.9: Examples of Contextual Misclassification: Supportive Language Misidentified as Loneliness Self-Disclosure in Kooth Forum Data (All posts predicted as "Lonely" with maximum confidence)

Post ID	**Content (Excerpt)**	**Prediction Probability**
73	**Self-disclosure:** "I agree. I am lonely BECAUSE i have no friends... For me loneliness is having no friends..."	1.00
3407	**Self-disclosure:** "exactly how I've been feeling ever since my boyfriend left me- he was my only friend and now I have no one..."	1.00
2667	**Supportive:** "we'll all be your friends! you're never alone"	1.00
2049	**Self-disclosure:** "I feel empty and lonely all the time - even with people around me..."	1.00
4077	**Supportive:** "i feel the exact same as you. ur not alone"	1.00
9933	**Supportive:** "I'm feeling the exact same as you you are not alone"	1.00
30	**Mixed:** "Though we are all surrounded by people, we often tend to feel lonely... You just have to find the right person. So if you need someone to talk to, I'm here for you!"	1.00
2610	**Self-disclosure:** "This is me but only when my other Friend isn't here, she always talks about her and makes me feel lonely..."	1.00
4606	**Supportive:** "Heyyy, you're not alone darling x"	1.00
5696	**Supportive:** "you're not alone"	1.00
9803	**Supportive:** "ur not alone"	1.00

Note: **Bold** annotations indicate whether content represents genuine self-disclosure or supportive messaging. All posts were predicted as "Lonely" by the SVM classifier.

in Table 6.11.

These systematic misclassifications reveal fundamental limitations that extend beyond the technical capabilities of traditional approaches, pointing to concerning methodological issues in the underlying dataset collection practices that compromise construct validity in loneliness detection research.

Table 6.10: LLM Contextual Analysis of Posts Misclassified by the Traditional Model

ID	**Content (Excerpt)**	**LLM Reasoning**
73	"I agree. I am lonely BECAUSE i have no friends... For me loneliness is having no friends..."	Model error - no reasoning provided
3407	"exactly how I've been feeling ever since my boyfriend left me- he was my only friend and now I have no one..."	Explicit mention of loneliness following a breakup. Evidence of lacking companionship and emotional support.
2667	"we'll all be your friends! you're never alone"	The post reassures others they are not alone, indicating concern for others rather than personal loneliness.
2049	"I feel empty and lonely all the time - even with people around me..."	The individual explicitly states feelings of loneliness. Despite being surrounded by people, they describe feeling isolated.
4077	"i feel the exact same as you. ur not alone"	The post focuses on supporting another person. Words such as 'ur not alone' suggest empathy rather than self-disclosure of loneliness.
9933	"I'm feeling the exact same as you you are not alone"	The post reassures others and expresses empathy, indicating supportive intent rather than personal loneliness.

Note: All posts were predicted as "Lonely" with maximum confidence (1.00) by the SVM model. LLM reasoning demonstrates contextual understanding where available, but consistency issues are evident with missing explanations for some predictions.

6.7 Discussion

6.7.1 Traditional Model Performance and Methodological Considerations

The traditional models achieved high accuracy scores (Table 5.2), with several models approaching 100% performance in loneliness classification. At first glance, these results might suggest that traditional approaches successfully predict loneliness expression, particularly given that feature importance analysis reveals intuitively relevant terms such as "lonely," "alone," and "friends" (Figure 6.8). However, these high accuracy scores raise concerns about model validity. The fact that an LR model can identify a nuanced and subjective emotional state, such as loneliness, with near-perfect accuracy suggests that the model may be detecting patterns other than genuine linguistic indicators. This analysis demonstrates how surface-level evaluation of ML models and associated FI can lead to incorrect interpretation of model capabilities. While the FI appears to validate the approach, a deeper investigation reveals patterns that challenge the validity of the classification task.

Evaluating the Outputs From Kooth Data and Highlighting the Mislabelled Outputs

This analysis reveals that the traditional model struggles to differentiate between self-disclosures of loneliness and supportive posts that contain loneliness-related keywords. However, this limitation extends beyond the traditional classification models. An examination of the original Reddit dataset reveals post mislabelling that presents an initial explanation for the model's poor cross-domain performance. The training and test data contain numerous examples where supportive communication and community reassurance were incorrectly labelled as loneliness self-disclosure, as shown in Table 6.9.

These mislabelling patterns in the original dataset indicate why the SVM

Table 6.11: Qualitative Analysis of LLM Loneliness Classification Reasoning

Attribute	Example 1	Example 2	Example 3	Example 4
Content (Excerpt)	"My friends all kind of left out of the blue and blocked me on everything. I finally was able to ask them why, and all the reasons they gave were not my fault or were just 'I don't like you' without reason."	"I got really hurt when they left me, they just stopped without telling me, so I was left all alone..."	"I have so many different personalities and i cant juggle them for much longer."	"Loneliness is a matter of perspective. I never feel lonely by myself and i have spent over many days in isolation due to mental disabilities."
LLM Reasoning	Explicitly states feeling lonely through direct language. Describes emotional distress such as sadness and difficulty concentrating.	The post explicitly states feelings of loneliness when referring to the author's experience before meeting A. Statements like 'I felt really lonely' directly indicate loneliness.	The post does not explicitly mention loneliness but focuses on identity struggles and emotional states.	The post mentions prolonged isolation but explicitly states that the author does not feel lonely. The focus is on philosophical insights and self-improvement rather than expressing emotional distress.
Assigned Label	Lonely	Lonely	Not Lonely	Not Lonely

Note: Examples demonstrate LLM reasoning patterns in loneliness classification, showing both successful identification and nuanced distinction between isolation and loneliness.

model misclassified supportive language in the Kooth data. The model learned to associate phrases like "you are loved and cherished" and "I'll try my best to be there for you" with loneliness because these language patterns were incorrectly labelled as loneliness expressions in the training data. These results represent a form of dataset-induced confounding, where subreddit-based labelling practices created spurious associations between supportive communication and loneliness self-disclosure.

The presence of these labelling errors in both the training and testing sets demonstrates that the high accuracy reported in the original study likely reflects the model's success in learning these incorrect patterns rather than its actual capability for loneliness detection. These findings validate initial concerns about the reliability of loneliness detection research, given the insufficient manual validation of dataset quality.

6.7.2 LLM Performance and Methodological Considerations

While transformer architectures offer theoretical advantages for capturing semantic relationships between words in text, the empirical evaluation of LLMs for loneliness detection in this study yielded mixed results that highlight both potential benefits and limitations of current LLM classification approaches. The comparative analysis revealed that traditional approaches consistently outperformed LLMs in the binary classification task, with the best-performing SVM classifier achieving 96% accuracy compared to the fine-tuned DeepSeek model's 83% (Table 5.2 and **??**).

However, LLMs demonstrated capabilities that traditional approaches lack, particularly in generating reasoning outputs that provide contextual explanations for classification decisions. These explanations provide valuable insight for understanding indirect loneliness disclosures, offering insights into the patterns and semantic content that informed LLM predictions.

The granular loneliness disclosure classification results were particularly revealing of the limitations of LLMs. Fine-tuned models achieved substantially lower performance across all taxonomy dimensions compared to the original study findings (Jiang et al., 2022) (Table 6.4), further highlighting dataset-specific challenges, or the models' inability to learn these nuanced patterns. These findings must be interpreted cautiously, given the dataset quality concerns identified throughout this analysis, as the mislabelled training data may have constrained LLM performance.

Two critical conditions emerged for LLM effectiveness in mental health applications: first, training data must represent balanced, genuine examples of the target psychological construct rather than data-domain-specific patterns; second, fine-tuning approaches must be appropriately designed for the specific detection task. Without these conditions, even advanced language models may learn spurious associations rather than meaningful psychological indicators.

Based on the evidence of systematic mislabelling, cross-domain failures, and suspiciously high accuracy observed in Part 1 of this chapter, the author hypothesises that the LLM and traditional models are not predicting loneliness indicators, but rather the specific subreddit from which the post was initially collected (r/lonely or r/college). This potential for data-confounding requires a deeper analysis of the modelling results, without subreddit labels for each post, there is no direct way of initially identifying what is driving these predictions[1].

6.8 Part 2: A Framework for Identifying Dataset-Induced Confounding

Currently, there is no approach to identify dataset-induced confounding. This chapter defines a framework for the thorough evaluation of NLP models to identify data-confounding. Part one demonstrated that the Reddit dataset yields

[1]An attempt was made to contact the original authors of the paper, the data originated from (Jiang et al., 2022), to acquire the subreddit labels. However, there was no response from the corresponding author

misleadingly accurate classifiers and models that are non-generalisable. A critical question remains to understand why this is the case and how researchers can prevent these issues in the future. Through the continued analysis of the Reddit dataset, a published dataset that exemplifies these methodological problems has been published without the identification or disclosure of such issues. Furthermore, this work demonstrates how problematic datasets can be published and widely used without proper identification or disclosure of confounding issues, compromising research quality and negatively affecting mental health practice and policy.

6.8.1 Critical Analysis of Existing Data Collection Methodological Practices

Jiang et al. (2022) presented a granularly labelled dataset of Reddit posts that identifies loneliness self-disclosed. These granular labels were developed based on a taxonomy proposed by (Kivran-Swaine et al., 2014) and further expanded upon by Jiang et al. (2022). However, Jiang et al. (2022)'s study exhibits three significant limitations which need careful examination, as these limitations establish the framework for the subsequent ablation framework defined in this chapter.

1. The first limitation pertains to the author's lack of a detailed investigation into the high accuracy classification rates. Two of their implemented models achieved 99% accuracy in distinguishing lonely and non-lonely posts (Table 6.12); however, this performance received minimal methodological scrutiny in their analysis. Such high accuracy scores in any NLP task identifying subjective emotional experiences should result in further analysis to identify over-fitting or spurious feature correlations.

2. Secondly, a further limitation (as demonstrated in Part 1 subsection 6.6.2 and section 6.7.1) pertains to the mislabelled observations in which posts

encouraging or supporting other Reddit users in their struggle with loneliness (i.e. "You are not alone").

3. The most critical limitation is the absence of a feature identifying the originating subreddit of each post. This limitation is particularly puzzling due to the inclusion of a clustering visualisation that explicitly denotes model performance across specific subreddit communities (See Appendix G). This prevents the study from being reproducible, as there is no means of validating whether their models learned to classify loneliness or to distinguish between the subreddits.

These limitations directly inform the methodological approach undertaken in this chapter, where cross-algorithm evaluation and ablation analysis examine whether high-performing loneliness detection models learn genuine psychological indicators of loneliness or the linguistic markers of specific subreddits. This diagnostic framework provides researchers with tools to identify and validate construct validity in computational mental health research through the combination of granular feature importance and ablation analysis.

Table 6.12: Performance Summary of Loneliness Binary Classification Models

Model	**Accuracy**	**Precision**	**Recall**	**F1-Score**
LSTM Baseline	0.90	0.89	0.90	0.89
BERT + MLP	0.97	0.95	0.99	0.97
HDLN	**0.98**	**0.96**	**0.99**	**0.97**

Note: Performance metrics shown are Accuracy, Precision, Recall, and F1-Score. **Bold values** represent the highest performance achieved for each metric. Results reproduced from (Jiang et al., 2022) for the loneliness binary classification task.

6.8.2 Evaluating Feature Importance in NLP Classification Models

Feature importance analysis seeks to identify the features which drive the prediction of the outcome feature (Lai et al., 2019). There are several ways FI can be identified. Typical model FI is identified by the coefficients of the implemented algorithm (LR, SVMs or RFs), although these are model-specific. There are model-agnostic approaches to identify FI, such as SHAP. In the context of this chapter, the features are the words in the Reddit posts that drive classification. When evaluating text data, it is crucial to evaluate multiple FI approaches as different FI metrics can generate contrasting outputs (Doshi-Velez & Kim, 2017; Lai et al., 2019). While FI can provide insight into drivers of model prediction, it does not identify any underlying biases or spurious model results that arise from poor data collection practices or problem formulations, such as demographic or data source confounding.

PI is a model-agnostic FI technique that measures how much each feature contributes to a model's predictive performance by systematically disrupting the relationship between that feature and the target variable. This disruption is achieved through the randomisation of the outcome features (loneliness) and its associated input feature (words within a Reddit post).

In this study, I both propose the importance of and implement "Ablation Analysis". Ablation is an additional step in the ML experiment process to provide evidence of what specific signal a model is detecting in a given dataset. Ablation is typically applied in medical studies, such as tissue ablation, which involves the targeted removal of tissue to treat diseases or understand biological function (Keum et al., 2024). However, the core principle remains the same in ML modelling, systematically removing components to understand their individual contributions to the overall system or phenomenon being studied. In ML, ablation approaches can be applied to improve model accuracy through recursive feature elimination and PI (Sheikholeslami et al., 2021). While there are frameworks for ablation approaches in deep learning (Meyes et al., 2019; Sheikholeslami et al., 2025), such as ablating model components and features across specific elements of deep learning architectures to understand model output (Clark et al., 2019), there is little research on the impact of ablation in text classification studies.

The potential impact of ablation is highlighted by Lipton and Steinhardt (2019), who discusses how a lack of ablation approaches can result in researchers overrepresenting research contributions and potentially misleading readers. Lipton & Steinhardt identify the benefits of ablation, in which a more rigorous understanding can come from robustness checks as well as qualitative error analysis. This combination of increased rigour and more granular error analysis can enable the detection of bias in several ML contexts, including model training efficiency and classification accuracy.

6.8.3 Detecting Predictive Bias in Classification Approaches

Bias can manifest in various ways across ML datasets. A quintessential example of bias in data is presented (Esteva et al., 2017) in which they report training an algorithm to detect Malignant melanoma correctly in 91% of cases. However, this high predictive performance was actually an artefact of bias in the dataset, in which some photos of skin lesions contained rulers, and others did not, and this is the signal the model was detecting, rather than cancerous or non-cancerous lesions. The authors published a follow-up paper identifying the issue of bias in ML for image analysis (Narla et al., 2018), raising awareness of the bias that can be generated from image artefacts and image quality on melanoma classification was covered in detail with researchers (Akkoca Gazioğlu & Kamaşak, 2021).

These bias issues are present in NLP studies, such as the potential bias in healthcare record analysis (Gianfrancesco et al., 2018), in which the different linguistic styles used by different healthcare providers in healthcare records can result in models. While multi-source validation, demographic stratification, and shortcut learning tests are recommended (Cross et al., 2024), these are not standard practice, resulting in spurious pattern learning to remain hidden until real-world deployment reveals the biases.

Researchers in the field of medicine are aware of the impact of potential bias;

social scientists and psychologists should also be aware of the impacts of bias in the data they collect and be able to identify bias by applying the defined framework in this chapter.

Shah et al. (2020) proposed the Predictive Bias Framework, which differentiates potential sources of bias across a standard supervised NLP pipeline. Covering a broad range of predictive biases, this chapter's analysis identifies an additional, previously uncharacterised bias type, dataset-induced confounding. This bias arises when a model learns systematic differences present in a dataset (e.g., source community or platform-specific language) that correlate with the outcome feature but are not causally related to the construct being evaluated. Table 6.13 adapts Shah et al. (2020)'s framework to the mental health NLP domain, providing examples for each bias category.

Table 6.13: Types of Bias in Natural Language Processing Pipelines

Bias Type	**Description**	**Mental Health NLP Example**
Semantic Bias	Unintended associations between words and social categories	Models linking loneliness expressions with gender-specific vocabulary
Selection Bias	Sample observations not representative of either the wider application population or the underlying data source's user base.	Training data drawn disproportionately from specific online communities (e.g., r/lonely and r/college) or time periods, resulting in models that do not generalise to the broader population or even the wider platform user base
Over-amplification	Models exaggerate associations between certain features and the prediction target, producing stronger correlations than actually exist in the data	A classifier trained on subreddit posts over-predicts loneliness for young male users, because the training data overrepresented that subgroup
Label Bias	Biased annotations or latent bias from past classifications	Mislabelling supportive communication as loneliness expression
Dataset-induced Confounding	**Models learn data sources rather than target constructs due to systematic collection error**	**Learning subreddit origin (r/lonely vs r/college) instead of loneliness**

Note: Bias types adapted from Shah et al. (2020), expanded with dataset-induced confounding as identified through this chapter's current analysis.

Shortcut learning and spurious correlations are well-documented phenomena across ML domains, including computer vision and text analysis (Geirhos et al., 2020, 2022). Similar to computer vision tasks where spurious correlations may involve texture bias (as identified by Geirhos et al. (2022)), mental health models must distinguish between linguistic psychological indicators and community-specific linguistic patterns (Shah et al., 2020). While often contextualised within deep learning approaches, this issue can manifest regardless of the ML approach. This study builds on established bias detection frameworks to provide a systematic methodology for identifying dataset-induced confounding, specifically in psychological construct detection tasks.

6.9 Feature Ablation Framework for Confounding Detection

The consistently high performance achieved across all model architectures (traditional and LLM) suggests that dataset-induced confounding is occurring rather than loneliness construct detection. The observed pattern where models achieve near-perfect accuracy in distinguishing between loneliness and non-loneliness posts raises fundamental questions about what linguistic features are actually driving these classifications. The proposed ablation framework systematically investigates this confounding by examining whether high predictive performance depends on subreddit-specific linguistic markers that are incidental to the expression of loneliness. Crucially, expressing the absence of loneliness should not require domain-specific vocabulary related to academic settings (such as “college” or “university” terminology). Yet, a preliminary FI analysis (shown in section 6.5.3) suggests that these domain-specific words feature prominently in classification decisions.

To detect dataset-induced confounding, this chapter proposes a Granular Feature Importance and Ablation Analysis Framework. This framework extends the Predictive Bias Framework defined by Shah et al. (2020) by integrating FI analysis with systematic feature ablation to identify and remove spurious predictive signals before model interpretation.

The framework consists of two analytical steps:

1. **Granular Feature Importance Analysis:** This step identifies features with the strongest associations to the target label using global feature importance metrics such as model coefficients for linear models or Gini importance for tree-based models.

   (a) Calculate global importance metrics for all features

   (b) Rank features by absolute importance scores for each outcome class

   (c) Conduct qualitative analysis of top-ranking features to identify potential indicators of dataset-induced confounding

2. **Feature Contribution Analysis:** This step applies SHAP analysis both before and after the removal of the top predictive model features (defined by absolute feature importance metrics).

   (a) Apply baseline SHAP analysis to the original feature set

   (b) Remove top 20 predictive features as defined by the absolute importance scores

   (c) Re-apply SHAP analysis on the reduced feature set

   (d) Compare SHAP outputs to assess prediction and feature contributions

   (e) Identify if spurious patterns are present

Examining absolute FI values for each class addresses a fundamental question in NLP-based mental health research: *are the linguistic features driving predictions toward each outcome semantically meaningful for the construct being modelled?* Answering this requires identifying what constitutes spurious patterns. Spurious patterns are identified as features that lack theoretical grounding, such as having no established connection to loneliness in psychological literature, or that reflect data collection artefacts (e.g., platform-specific terms or methodological confounds from the data collection process).

Ablating the top 20 features removes the primary words driving predictions. This removal reveals whether the model relies on linguistic indicators of loneliness or spurious patterns, which would be evidenced by performance collapse or shift to features unrelated to loneliness self-disclosure.

By applying these steps in this study, this framework approach reveals that high predictive performance in the Reddit dataset is substantially driven by dataset-induced confounding, rather than genuine linguistic indicators of loneliness.

6.10 Ablation Results

6.10.1 Step 1: Feature Importance Examination

Model FI scores were extracted from the LR model to identify the most discriminative linguistic features for each class (lonely or not-lonely). The LR was selected due to the direct interpretability of the model coefficients, which provide clear insights into how specific words contribute to classifications. This transparency is essential for identifying potentially spurious correlations in the learned patterns. Figure 6.9 shows the top 20 features with the strongest positive weights (left panel, green gradient) and negative weights (right panel, red gradient) from the optimised LR model. Positive weights indicate features that push the LR decision boundary toward loneliness prediction, while negative weights indicate features that favour non-loneliness classification.

The analysis reveals distinct semantic clustering: loneliness-predictive features are dominated by emotional and social terminology ("lonely": 17.46, "alone": 14.59, "friend": 8.92), while non-loneliness-predictive features consist primarily of academic and practical vocabulary ("college": -5.04, "major": -3.80, "assignment": -3.61). This pattern suggests the model may have learned to distinguish between different community discourses (emotional support forums vs. academic discussions) rather than universal loneliness indicators, highlighting potential dataset-induced confounding in the model. However, the substantial magnitude difference between the strongest positive weight ("lonely": 17.46) and the strongest negative weight ("college": -5.04) indicates that emotional terminology provides more discriminative power for loneliness detection than academic terminology provides for non-loneliness classification.

Figure 6.9 also shows that the features driving non-lonely predictions are not semantically related to disclosures of non-loneliness, such as companionship terminology (e.g, "girlfriend", "boyfriend", "together") or expressions of social fulfillment (e.g, "loved", "supported", "belonging") which presents further justification to critically evaluate the model's performance and broader data quality.

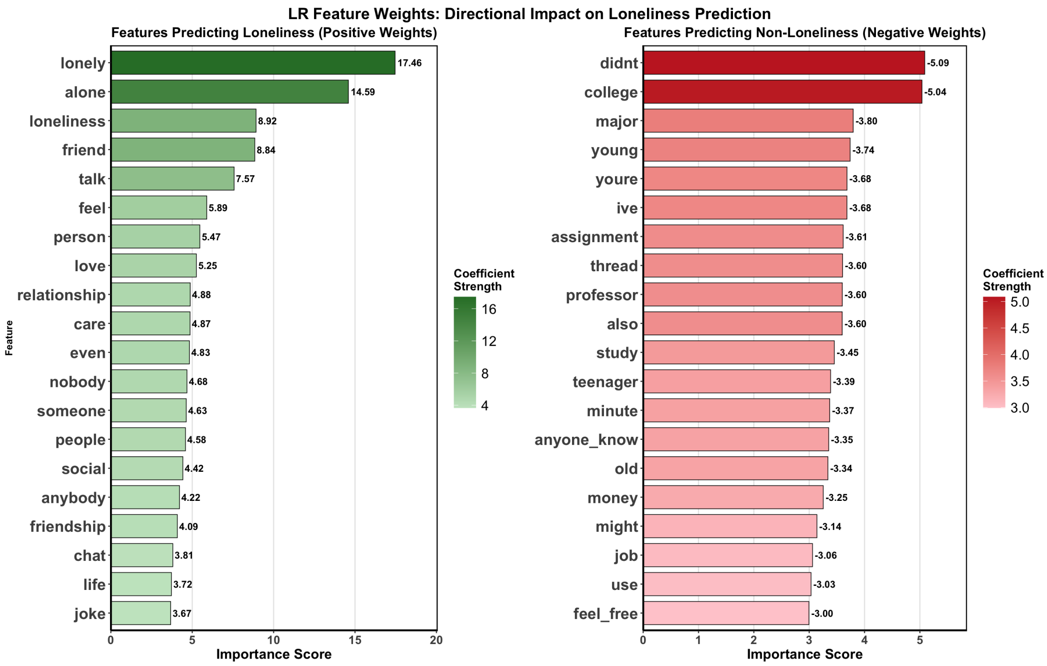

Figure 6.9: *Logistic regression feature weights showing directional impact on loneliness classification decisions. The green bars represent the features that drive predictions towards lonely classification, and the red bars show the features which drive model predictions towards the non-lonely class. The "Importance scores" are the feature weights derived from the model.*

6.10.2 Step 2: SHAP Feature Importance Ablation Analysis

The second step applies SHAP analysis both before and after the systematic removal of the most predictive model features (defined by absolute FI coefficient values). Comparing these outputs allows for the assessment of each feature's contribution to model predictions and highlights whether the observed performance is driven by spurious patterns embedded in the data.

Following ablation of the top 20 features (ranked by absolute coefficient value), the model was retrained and re-evaluated. The results demonstrate a performance decline: accuracy and F1-Scores dropped from 94% to 91%, across both non-ablated and ablated models (Table 6.14). This 3 percentage point accuracy drop aligns with the cumulative PI scores of the removed features, validating consistency between ablation and permutation analysis approaches.

Table 6.14: Performance Comparison of Non-Ablated vs Ablated LR Models

Model Configuration	**Accuracy**	**Precision**	**Recall**	**F1-Score**	**ROC AUC**
Non-Ablated LR	**0.94**	**0.94**	**0.94**	**0.94**	**0.98**
Ablated LR	0.91	0.91	0.91	0.91	0.96
Performance Drop	-0.03	-0.03	-0.03	-0.03	-0.02
Relative Decrease (%)	-3.2	-3.2	-3.2	-3.2	-2.0

Note: Comparison between the full LR model (non-ablated) and the model with top 20 features removed (ablated). **Bold values** represent the superior performance for each metric. Performance drop indicates the decrease in performance when key features are removed, demonstrating that model effectiveness was dependent on potentially spurious domain-specific features.

The SHAP analysis reveals a shift in FI patterns following ablation. In the original model (Figure 6.10), loneliness-specific terminology such as "lonely", "friend", and "alone" were the highest-weighted features for positive predictions, while academic terms such as "college" and "class" contributed to negative predictions. However, after removing these explicit loneliness indicators (Figure 6.11), the model's decision boundary becomes reliant on academic vocabulary, with terms such as "class", "major", "semester", and "student" serving as strong predictors of the not-lonely class.

This pattern suggests the model may be learning to distinguish between subreddit communities (emotional disclosure versus academic discussion) rather than identifying loneliness-related psychological states. The prominence of university adjacent terminology in driving not-lonely classifications indicates that the model's high accuracy may be partially attributable to subreddit-specific linguistic patterns rather than generalisable loneliness detection.

The SHAP values reveal both the importance and directionality of features, demonstrating how specific words contribute to classification outcomes (lonely vs. not-lonely predictions). Unlike aggregate coefficient analysis, SHAP enables observation-level examination of feature impacts, revealing systematic patterns across individual posts.

The non-ablated SHAP summary plot (Figure 6.10) exposes clear groupings of emotional vocabulary consistently driving loneliness predictions, while university and college terminology consistently favours non-loneliness classifications. This domain confounding becomes further apparent following feature ablation. After removing the top 20 features (Figure 6.11), the model's reliance on academic vocabulary increases, with terms such as "class", "major", and "semester" becoming primary drivers of non-loneliness predictions. These findings provide evidence for dataset-induced confounding, where high classification accuracy reflects successful subreddit identification rather than meaningful loneliness detection. It is clear that the model determines its classification of posts based on whether the language used relates to emotional self-disclosure or college, rather than distinguishing between lonely and non-lonely Reddit posts.

Crucially, it is clear that the driving features are also not semantically related to the disclosure of loneliness, and the experience of not being lonely, in that it would be expected that semantically the features that contribute towards being "Not Lonely". Words such as "friend" and "love" still drive the prediction towards lonely, while "class" and "professor" drive the prediction towards non-lonely prediction outcomes.

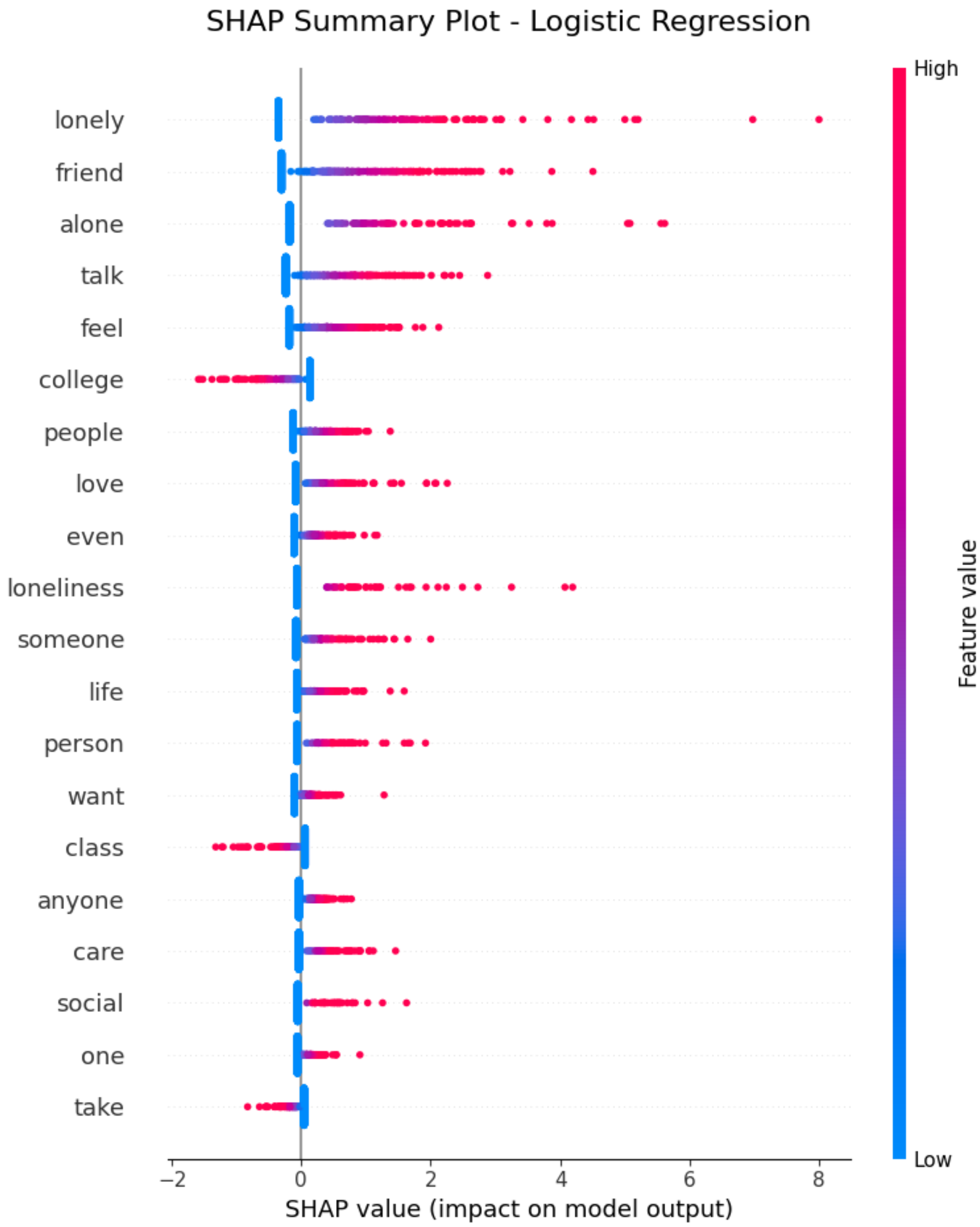

Figure 6.10: *SHAP summary plot for logistic regression showing feature importance and directionality for the top 20 predictive features. Features with positive SHAP values (right of zero) contribute to loneliness predictions; features with negative values (left of zero) contribute to non-loneliness predictions.*

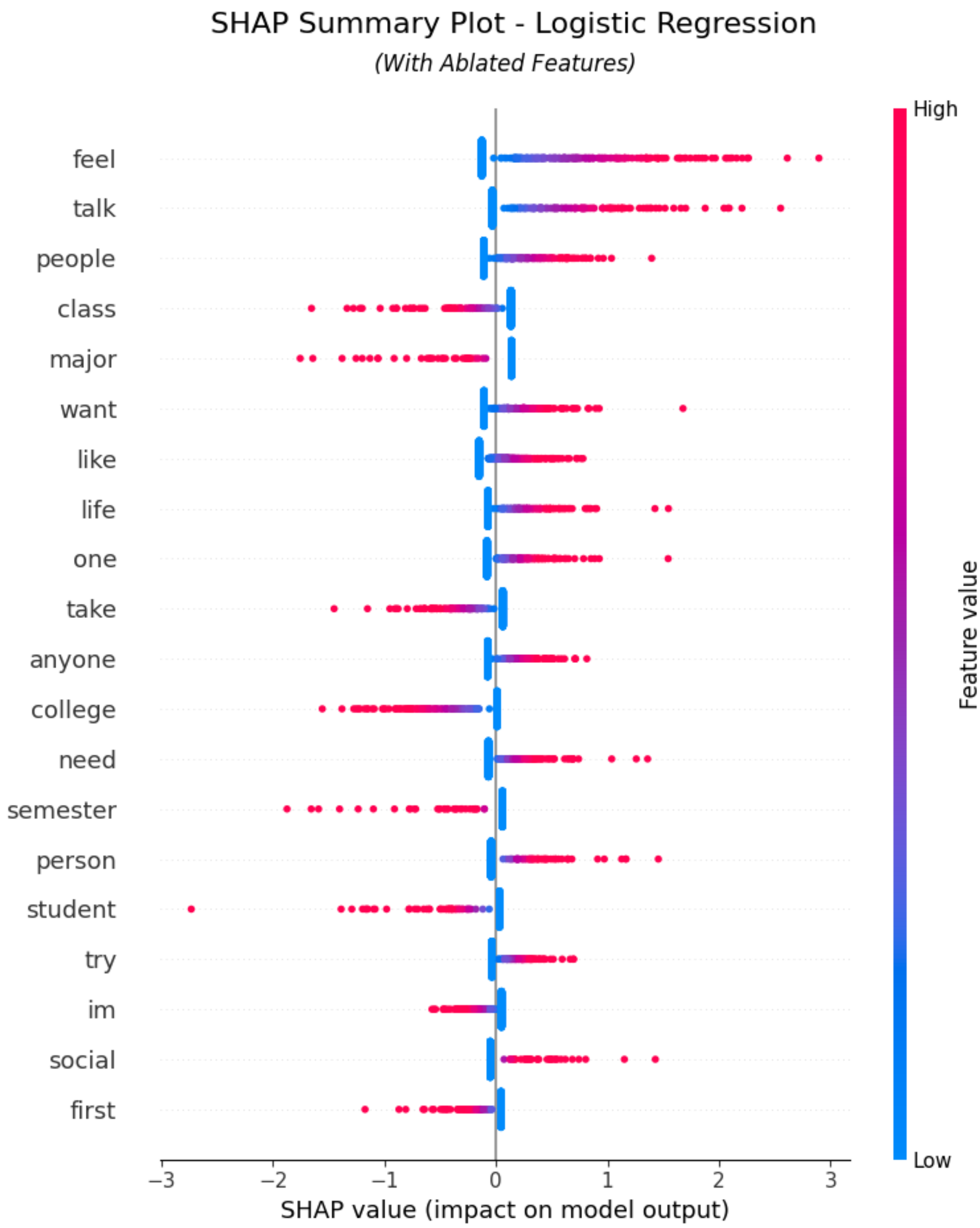

Figure 6.11: *SHAP summary plot for logistic regression (**With Top 20 Features Ablated**) showing feature importance and directionality for the top 20 predictive features. Features with positive SHAP values (right of zero) contribute to loneliness predictions; features with negative values (left of zero) contribute to non-loneliness predictions.*

6.11 Discussion of Dataset-Induced Confounding Evidence

The evidence presented in this chapter reveals a fundamental challenge facing computational mental health research: what appears to be accurate construct detection may actually reflect systematic data collection biases.

6.11.1 The Limitations of Surface-Level Feature Validation

The initial FI analysis (Figure 6.8 and Figure 6.9) highlights terms related to explicit loneliness self-disclosure (e.g., “lonely”, “alone”, “friend”). Such results are unsurprising, given that the dataset labels were assigned on the basis of self-disclosure predominantly comprising these keywords. Feature importance analysis may therefore provide misleading model validation, as the prominence of construct-relevant terms can mask underlying methodological flaws.

This reliance on surface-level keyword validation extends beyond this dataset. Similar dependence on overt self-disclosure terms appears in prior studies of online loneliness expression (e.g., “I’m so lonely”, “I feel left out”, “I feel isolated”) Guntuku et al. (2019), Kiritchenko et al. (2020), and Kivran-Swaine et al. (2014), as well as in established psychometric tools such as the UCLA Loneliness Scale, which includes items containing words like “friends” or “nobody.”

Applying the analytical framework developed in this chapter reveals a concerning pattern. Rather than the >90% accuracy in predicting nuanced emotional experiences of loneliness reported by Jiang et al. (2022) or demonstrated in this chapter (see Table 5.2), the evidence reveals dataset-induced confounding. This analysis reveals distinct feature distribution patterns across outcome classes, indicating that the models capture domain-specific linguistic markers rather than loneliness and self-disclosure. These findings highlight broader methodological concerns in mental health NLP data collection.

6.11.2 Methodological Recommendations for Data Collection in Mental Health NLP

As demonstrated in subsection 6.2.2 and subsection 6.8.1, data are typically scraped from accessible sources such as X or Reddit without adequate consideration for potential confounding variables. While some loneliness studies acknowledge these dataset limitations or contextualise their methodological approaches accordingly (such as topic clustering (Andy, 2021)), this remains a fundamental challenge. This issue should be addressed through more rigorous data collection protocols and specific labelling of the phenomena being modelled, ensuring study results are appropriately applicable to policy and practice contexts.

This analysis demonstrates that without systematic investigation of data-confounding, researchers may unknowingly develop models that learn domain-specific patterns rather than psychological constructs. To mitigate these risks, this chapter proposes the following methodological framework for mental health NLP data collection:

Core Principles for Digital Text-based Data Collection:

1. **Source Consistency:** Collect all samples from one data source and apply content-based labelling

2. **Representative Sampling:** If multiple sources are being used, ensure data represents the broader target population rather than specific communities

3. **Constructing Comparison Samples:** When constructing comparison samples, ensure data represents diverse contexts and communities to prevent domain-specific linguistic patterns from confounding the target construct

Implementation for Reddit-based Research:

1. **Single-source approach:** Collect all posts from one subreddit (e.g., r/mentalhealth) and label based on content analysis rather than subreddit membership

2. **Multi-source approach:** When representing "non-lonely" samples, draw from multiple diverse subreddits to prevent over-representation of specific communities (e.g., academic, gaming, hobby subreddits)

Researchers should apply the diagnostic framework outlined in section 6.9 to identify potential dataset-induced confounding in their datasets. While some research designs intentionally compare distinct communities (Andy, 2021), studies claiming to detect psychological constructs must validate that models learn mental health disclosure indicators rather than community-specific discourse patterns.

6.11.3 Implications for Policy and Research

The paper presented by Jiang et al. (2022) presents initially compelling results, given the complexity of the implemented methods, the high accuracy scores that Part 1 of this chapter replicates, and the calibre of both the conference venue and the authors' institutional affiliations. Without the systematic analysis applied in Part 2 of this chapter, the fundamental issues with the dataset would have remained hidden behind complex methodological classification approaches and high model performance. It is clear that the dataset published by Jiang et al. (2022) has fundamental flaws, which render it unsuitable for analysis and necessitate its rescission to minimise the negative impacts of any conclusions drawn from this data.

These factors create a particularly concerning scenario for the broader research field of computational mental health analysis. It is not unreasonable that researchers seeking granularly labelled datasets for loneliness self-disclosure would discover this resource during a literature or data review (as I did), especially given the scarcity of such labelled datasets. These researchers might then perform similar analyses or train text classification models using this data to make inferences about other datasets or populations.

Such applications could initiate a cascade of methodologically flawed research with genuine consequences for policy and practice in loneliness intervention and mental health screening. Well-meaning researchers, lacking the resources or expertise to conduct the comprehensive methodological investigation presented here, might unknowingly propagate these fundamental data quality issues throughout the field.

These findings underscore an urgent need for standardisation in both data collection and analysis approaches within computational social science. Without such standardisation, dataset-induced confounding combined with surface-level model evaluations risk transforming well-intentioned mental health research into baseless research outputs that could misdirect policy and practice away from rigorous evidence-based approaches. The implications also encompass the real-world effectiveness of interventions designed to address loneliness.

Extending the Loneliness Taxonomy

This chapter identified the limitations of the loneliness taxonomy in subsection 6.2.3, in terms of overlapping concepts across the Interpersonal dimension and the clarity needed for the Somatic Loneliness context, and suggests an extension to this framework (See Figure 6.12). When labelling lonely posts, it is necessary to include a feature that identifies whether the disclosure of loneliness is direct or indirect. This can enable the modelling of the more nuanced disclosure of loneliness and overcome this limitation across the research domain, in which a critical element of loneliness remains unlabelled.

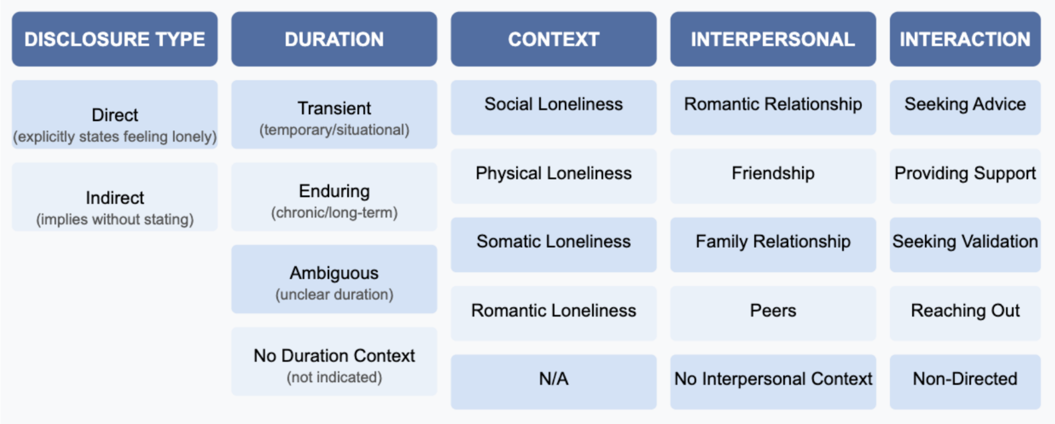

Figure 6.12: *Granular Loneliness Labelling Taxonomy With Additional Disclosure Type Dimension*

6.11.4 Limitations and Future Work

This chapter has identified a range of limitations with both the implemented modelling approaches and the data collection approaches. While LLMs demonstrated potential through the reasoning capabilities of the DeepSeek LLM model, consistency issues affected performance across both base and fine-tuned versions. Moreover, the data-confounding issues identified in this chapter obscure whether model predictions reflect genuine semantic patterns or merely distinguish between data sources.

The traditional models, despite achieving high accuracy, demonstrate limited practical utility by basing predictions on simple keyword presence (e.g., ‘alone’ indicates loneliness, ‘college’ indicates non-loneliness).

Despite these limitations, this chapter offers several avenues for future research, both in terms of the model class exploration and dataset collection approaches for mental health analysis. Particularly, the promise of future LLM analysis and the potential insight this can offer researchers and practitioners if rigorously applied with increased model output consistency.

There is also the application of the enhanced loneliness labelling taxonomy (See section 6.11.3 and visualised in Figure 6.12), which can be applied to a rigorously collected dataset following the framework defined in subsection 6.11.2.

The feature analysis framework (outlined in section 6.9) can also be applied in future studies to detect dataset-induced confounding before researchers present their results, thereby minimising published mistakes and demonstrating the efficacy of researchers' data collection. Additionally, this framework can be applied retrospectively to a range of previously undertaken loneliness NLP analyses to identify potential confounding factors in previously analysed datasets.

6.12 Conclusions and Implications

This chapter demonstrates both the feasibility and importance of detecting self-disclosure of loneliness in forum data using traditional and contemporary NLP approaches. Importantly, it revealed how inadequate data collection and labelling practices fundamentally compromise research validity in this particularly sensitive domain, and that Jiang et al. (2022)'s reported results were incorrect. Given that loneliness research necessarily examines stigmatised experiences, maintaining rigorous methodological standards is essential for preserving trust between researchers, clinicians, and the public.

While both traditional and LLM approaches showed promise, robust methodological evaluation requires more rigorously collected datasets. Future work must address data confounding issues to enable meaningful comparison of model performance without the methodological constraints identified in this analysis.

Part 1 established the comparative performance of traditional ML models and LLMs for loneliness prediction, identifying the specific strengths and limitations of each approach while providing clear guidance for future loneliness detection research.

Part 2 revealed systematic flaws in standard data collection approaches across the loneliness and self-disclosure literature, compromising the generalisability of research and the broader understanding of loneliness experiences. Through granular dataset analysis, this chapter exposed these limitations and their consequences for construct validity. Crucially, this work developed and validated a systematic ablation methodology that exposes spurious correlations in text classification models, establishing a practical framework for assessing construct validity in computational mental health research. The empirical analysis revealed that high model performance masks fundamental validity issues—despite consistently strong performance across traditional ML models, current approaches primarily detect domain-specific discourse patterns rather than specific loneliness indicators, providing researchers with concrete tools to prevent dataset-induced confounding in future studies.

To mitigate these identified data-confounding issues in loneliness self-disclosure NLP, this chapter established a novel diagnostic framework applicable to any text-based dataset. The prevention of these concerns requires implementing the principles of data collection (identified in subsection 6.11.2) alongside the three-step ablation framework (section 6.9).

These contributions provide computational mental health researchers with practical tools to identify confounding issues and methodological principles to prevent them. By establishing rigorous validation approaches, this work enables mental health NLP research to move beyond surface-level pattern recognition toward more valid detection of psychological constructs.

Chapter 7

Discussion and Conclusion

7.1 Main Contributions

This thesis comprised four interconnected studies that critically employed a mixed-methods approach to examine loneliness at both individual and population levels.

The mixed-methods approach enabled a qualitative understanding of practitioners' perspectives through semi-structured interviews, which revealed patterns of indirect expression of loneliness. At the same time, the quantitative analysis of the large-scale survey quantified the independent impact of stigmatised deprivation on loneliness experiences. Natural language processing (NLP) analysis of digital mental health forum data and social media posts provided methodological frameworks for detecting latent indicators of loneliness while identifying fundamental validity issues in existing research approaches. This integrated methodology enabled a comprehensive examination of loneliness across multiple contexts within digital mental health provision.

This thesis advances the understanding of loneliness in digital mental health contexts through further evidence of stigma as a primary barrier to direct loneliness disclosure in therapeutic settings. Furthermore, this shows that loneliness is exacerbated by specific types of deprivation, highlighting how demographics, such as *income* are too coarse to enable a genuinely nuanced understanding of loneliness. By analysing practitioner insights alongside large-scale quantitative data, this research reveals how indirect expressions of loneliness align with the broader needs of service users (SUs) in digital mental health interventions, such as wanting "*to feel heard*" or "*to build support systems*" which represent the predominant pattern of indirect loneliness communication in digital therapeutic environments as identified by practitioners.

However, and potentially even more importantly, this research highlights critical methodological limitations in current computational analysis approaches to loneliness detection, particularly in data collection and validation practices used in social media-based analysis studies. Through a systematic analysis of an existing dataset, this work demonstrates how poor data collection protocols can produce models that appear to perform well but actually learn spurious correlations rather than indicators of loneliness experienced.

Crucially, these findings and contextualisation would not have been possible without the input and data access of the digital mental health intervention **Kooth**. Industry collaboration helps support and contextual findings to enable both research impact and the cohesive combination of mixed-methods approaches, which are crucial for understanding nuanced concerns *such as loneliness* in real-world environments.

7.1.1 Summary of Thesis Contributions

Table 7.1: Summary of Thesis Contributions to Loneliness Research in Digital Mental Health

Study No.	Key Contribution	Chapter
1	Development of novel insights into the conceptualisation of loneliness and the indirect nature of loneliness disclosure in digital therapeutic contexts due to stigma, supported by practitioners	Chapter 3
2	Development, validation, and real-world implementation of the Adult SWAN-OM. Now actively used in Kooth's digital mental health intervention practice, addressing the gap in actionable single-session outcome measures	Chapter 4
3	Identification and quantification of "stigmatised deprivation" as an independent predictor of loneliness beyond traditional socioeconomic measures	Chapter 5
4	Development of a novel framework for detecting dataset-induced confounding in NLP mental health research, exposing critical validity issues where high-performing models learn spurious domain patterns rather than genuine psychological indicators	Chapter 6

7.1.2 Aligning the Research Questions with Each Study

The matrix shown in Table 7.2 demonstrates the systematic approach undertaken across the four studies to address the preceding research questions. Each study serves a distinct but complementary role in building a further understanding of loneliness.

Question 1: How can digital mental health practitioners provide insight into loneliness in digital therapeutic contexts?

Chapter 2 (Study 1) provided the foundational evidence for Research Question 1, establishing through practitioner interviews that loneliness affects 80-90% of clients yet remains unexpressed due to stigma. This study also offered supporting evidence for subsequent Research Questions by identifying patterns of indirect expression (supporting RQ2 and RQ4) and contextual drivers, including stigmatised experiences (supporting RQ3).

Question 2: How are service user needs expressed in digital mental health interventions, and what methodological approaches can best capture them?

Chapter 3 (Study 2) directly addressed Research Question 2 by developing methodological approaches (NLP analysis, co-creation workshops) to capture latent expressions of service user needs. The Adult Session Wants and Needs Outcome Measure demonstrated how NLP methods can identify wants and needs that signal loneliness concerns, such as "to feel heard or understood." This study also provides supporting evidence for Research Question 1 by validating practitioner insights about indirect loneliness expression patterns through the developed outcome measure.

Question 3: What are the social and economic drivers of loneliness, particularly in relation to stigmatised lived-experiences?

Chapter 4 (Study 3) directly addresses Research Question 3, quantifying the independent impact of stigmatised deprivation on loneliness experiences through ML analysis of survey data. The identification of "stigmatised deprivation" as a predictor beyond conventional socioeconomic measures extends the qualitative findings from Study 1 into quantitative insights, demonstrating that stigmatised experiences create measurable psychological burden independent of general socioeconomic factors, increasing individuals' propensity to feel lonely.

Question 4: To what extent can traditional machine learning and large language models effectively identify loneliness self-disclosure in digital mental health forums?

Chapter 6 (Study 4) addressed research question 4 through a two-part investigation into loneliness detection approaches.

Part 1 evaluated the comparative effectiveness of traditional Machine Learning (ML) models and contemporary Large Language Models (LLMs) approaches for classifying posts containing loneliness self-disclosure. This analysis established the relative strengths and limitations of each methodological approach, providing empirical evidence for their detection capabilities in digital mental health contexts.

Part 2 conducted a critical methodological analysis of existing loneliness detection research. This investigation exposed fundamental flaws in data collection approaches within a published loneliness dataset and developed a systematic framework for detecting data-induced confounding. The analysis also reveals limitations in current labelling taxonomies, particularly the absence of granular labels distinguishing between direct and indirect disclosure patterns, a core finding supported by Study 1's practitioner insights. This study established both diagnostic tools for identifying methodological issues in existing datasets and preventive approaches for future data collection studies.

Table 7.2: Study-Research Question Cohesion Matrix

Research Question	**Study 1: Practitioner Perspectives**	**Study 2: Service User Wants and Needs & Outcome Measures**	**Study 3: Stigmatised Deprivation and Loneliness**	**Study 4: NLP Loneliness Detection Methods**
RQ1: How can digital mental health practitioners provide insight into loneliness in digital therapeutic contexts?	**Primary**	Supporting	-	-
RQ2: How are service user needs expressed in digital mental health interventions, and what methodological approaches can best capture them?	Supporting	**Primary**	-	-
RQ3: What are the social and economic drivers of loneliness, particularly in relation to stigmatised lived-experiences?	Supporting	-	**Primary**	-
RQ4: To what extent can traditional machine learning and large language models effectively identify loneliness self-disclosure in digital mental health forums?	Supporting	Supporting	-	**Primary**

7.2 On Loneliness and Stigma

While previous literature has explored the potential impact of and bi-directional relationship between stigma and loneliness (Barreto et al., 2022; Barry, 1962; Cooper, 2024; Madsen et al., 2021; Paton et al., 2024), this thesis has cemented the interconnected nature of stigma and the lived experience of loneliness. Through the interviews with practitioners in Study 1 and the ML analysis in Study 3, it is evident that stigma and stigmatised experience are closely intertwined with emotional loneliness. Understanding this bi-directional relationship reveals that loneliness in digital mental health contexts cannot be addressed solely via conventional social connection interventions (such as engaging in *Activity Group Interventions* or *Strategies for Personal Development* (Alvarez et al., 2025; O'Rourke et al., 2018; Zagic et al., 2022)), because loneliness operates through shame-based mechanisms rather than exclusively through a lack of social connection.

Study 1 revealed that two mechanisms of stigma related to loneliness: first, the shame associated with *being* lonely, which prevents direct disclosure; second, the impact *of* stigmatised experiences, which create social exclusion that generates feelings of loneliness.

In Study 1, practitioners consistently identified shame as a barrier to loneliness disclosure, noting "*a lot of the time I will pick up on real shame, real stigma and this idea of [...] if you're lonely, you're almost like Billy no mates*". This shame indicates why SUs use indirect language, such as "*I don't feel like I have anyone to talk to*", "*but I don't feel like anyone understands me*", rather than stating, "*I am lonely*". Practitioners also identified how other stigmatised experiences, particularly severe mental health episodes requiring hospitalisation (via involuntary admission) and experiences of deprivation, create social isolation that fosters experiences of loneliness.

Study 3 validated the impact of stigmatised experiences identified by the practitioners, showing food and energy insecurity were significant drivers of loneliness after illness and being unable to turn to friends and family, encapsulating the interconnected nature of the themes of *social isolation*, *illness*, and *stigmatised experiences* identified in study 1. This quantitative evidence confirms the practitioners' observations that specific hardships create psychological burden through shame-based social exclusion and "*othering*" beyond the effects of general deprivation. The independence of this relationship validates that stigmatised experiences operate as a distinct mechanism which drives loneliness. Together, these findings extend the theoretical understandings of loneliness by conceptualising loneliness as a stigma-based social experience. These findings also have direct implications for mental health practice, providing practitioners with insight into how loneliness manifests in digital mental health environments. These findings correspondingly extend to policy by identifying how loneliness is impacted by stigmatised deprivation.

7.2.1 The Consequence of Stigma for Mental Health Practice

The impact of this bi-directional relationship between stigma and loneliness is not limited to its impact on the individual, but also has consequences for the efficacy of mental health practice in terms of identifying loneliness within an intervention. As practitioners identified in Study 1 SUs very rarely self-disclose their experience of loneliness directly, often using metaphors, similes or higher-level mental health terms to describe feelings of loneliness.

Study 2 provided empirical validation of these indirect expression patterns through analysis of actual SU transcripts. Where practitioners observed clients saying "*I don't feel like I have anyone to talk to*" or "*I don't feel like anyone understands me*", the Adult SWAN-OM analysis revealed corresponding systematic patterns in SU wants and needs: "*Build my support system*", "*Feel heard or understood*", and "*Find a safe, non-judgmental space*". This convergence between practitioner observations and SU data demonstrates that shame-filtered expressions of loneliness follow identifiable patterns, enabling the development of detection approaches designed explicitly for therapeutic contexts where direct disclosure is rare.

These converging findings make a potentially significant contribution to mental health practice, as they demonstrate that loneliness and self-disclosure follow identifiable patterns across both practitioner observations and SU data. This convergence validates the findings that loneliness operates through predictable mechanisms which can be detected systematically (such as through the analysis of survey data captured in Study 3 and Text data evaluated in Study 4), offering novel insight for the detection and intervention of loneliness through digital therapeutic approaches.

7.3 The Lowering of Loneliness as a Priority for the UK Government

While this thesis' findings shed light on the theory of loneliness, as well as informing both practice and detection in text, they also offer broader insights for policy. Office for National Statistics (2025), show that in 2025 up to 28% of the British population report feeling sometimes, often or always lonely; with an estimated 8% of the population feeling lonely all of the time. These statistics show a consistent prevalence of loneliness across Great Britain (as identified in Chapter 2 section 2.5). While the ONS still estimates the national prevalence of loneliness, the Department for Culture, Media and Sport (DMCS) have not continued to publish their annual "Tackling Loneliness annual report" since the 30th of March 2023 (Department for Media Culture and Sport, 2023), suggesting a shift in priority in which loneliness is no longer seen as a governmental priority despite the swaths of evidence which identify it as a significant concern[1].

[1]It is worth noting that the cessation of loneliness-specific annual reports may reflect broader governmental priorities, such as fiscal constraints, administrative restructuring within DCMS, or strategic integration of loneliness considerations into wider mental health

7.3.1 Welfare Reforms and the Potential Impact on Loneliness

Throughout the course of this PhD, radical changes have been proposed to the social welfare mechanisms in Great Britain (Department for Work and Pensions & Government, 2025), which were particularly pertinent to the findings in Study 3 (Chapter 5). Two core changes proposed by the government include: 1. a tightening of those who are eligible for Personal Independence Payments (PIP), a payment for those receiving for individuals who have a long-term physical or mental health condition or disability, and 2. a reduction Universal Credit (UC), a payment for people under State Pension age and on a low income or out of work, specifically the UC payment given to those with health condition or disability who have difficulty working (for Work and Pensions, 2025).

According to definition of loneliness offered by Hawkley and Cacioppo (2010), in which loneliness emerges from discrepancies between desired and actual social relationships; the stigmatised deprivation identified in Chapter 5 as independently predictive of loneliness would be exacerbated by these welfare reforms, as reduced financial resources limit individuals' capacity to maintain social connections while the stigma associated with benefit dependency compounds both the emotional and social isolation components of loneliness.

While there is an underlying stigma around accessing social support, another reason to reduce poverty and provide more effective support is that those who are in poverty (food insecurity) face a higher prevalence of loneliness. There is also the impact of social support and the stigma associated with those living in poor-quality social housing, as well as the impact of subsisting exclusively on Universal Credit (Cheetham et al., 2019) and accessing food banks (S. Park & Berkowitz, 2024). There is a broader challenge which can prevent these insights from being enacted, which is the public perception of social

and social policy frameworks, rather than necessarily indicating a complete withdrawal of policy commitment. However, it is unclear if this is in fact the case.

support mechanisms (such as UC usage and foodbank usage) by the broader society. Why should those who use food banks or require subsistence from the government be shamed out of some minimal comfort?

Understanding stigma's role in loneliness requires acknowledging its deliberate nature in certain contexts. Dougherty et al. (2017) demonstrate this complexity in their finding that unemployed people are characterised by the public as "pathologically lazy and unmotivated", a stigmatisation that serves specific social and economic functions. This raises critical questions about the balance between stigma's social control mechanisms and its psychological costs, particularly in the context of loneliness policy.

This tension becomes particularly evident when considering that policies designed to address economic inactivity may inadvertently exacerbate the very social isolation they purport to alleviate. If welfare reforms increase stigma around UC receipt, and this stigma contributes to loneliness, then such policies may create a cyclical problem where economic measures designed to encourage self-sufficiency instead compound social disconnection. Understanding this dynamic is crucial for developing effective interventions to address loneliness, rather than merely treating its symptoms.

7.4 Linking The Experience of Loneliness to Data Through Machine Learning

While loneliness experiences can be identified and synthesised qualitatively through practitioner insights and service user disclosures, Chapters 5 and 6 evaluate loneliness quantitatively. Chapter 5 assesses the impact of stigmatised deprivation and demonstrates how ML approaches can identify features contributing to loneliness experiences.

Crucially, this thesis establishes that loneliness represents a latent concern that is inherently difficult to identify through conventional means. While AI approaches can detect loneliness indicators in text data, this work reveals several methodological challenges with broader implications for computational mental health research. The ability to identify latent psychological states, whether expressed directly or indirectly in text, is essential for detecting concerns without relying solely on demographic proxies.

Given that individuals rarely explicitly disclose loneliness in everyday contexts, these AI tools are vital for expanding research into latent societal problems and the broader category of psychological concerns.

These ML approaches provide empirical validation of theoretical propositions about loneliness mechanisms. While traditional loneliness scales such as the 20-item UCLA Loneliness Scale (D. Russell et al., 1978) measure the subjective experience of loneliness ("I feel left out", "I lack companionship"), it does not isolate which environmental, economic, or social factors are the primary drivers of these feelings for different populations. The feature importance evaluations traditional ML approaches offer, such as through SHAP (Shapley Additive exPlanations), enable the quantification of specific environmental, economic, or social factors (such as food insecurity, energy insecurity) that contribute to loneliness experiences, beyond correlational associations, to understand the directional impact of these factors.

For example, in the context of Chapter 5, the novel hierarchical ablation model enables the evaluation of theoretical predictions about how material deprivation creates the discrepancies between desired and actual social relationships central to loneliness theory (Hawkley & Cacioppo, 2010), affecting both the emotional and social dimensions of loneliness that Weiss identified (Weiss, 1975), while also revealing which aspects of deprivation carry the strongest predictive power for loneliness outcomes. However, these ML approaches can enable a more nuanced understanding of the broader experiences and contributing factors of the phenomenon under study. As with mental health concerns more broadly, these experiences are not like a broken leg, in which it is visible and there is a well-established approach to fix the ailment. This means, however, that there is an urgent need for appropriate labelling approaches to ensure that the ML models being trained and applied to understand loneliness can detect said loneliness signals in the data.

A Refinement of Loneliness Labelling Taxonomy

Following this need for high-quality data collection approaches to enable ML models to provide insight into loneliness, Chapter 6 focused on the challenge of correctly collecting social media posts for the mental health concern analysis (which applies to mental health concerns more broadly), and detected data-induced confounding. However, chapter 6 also implements methods to identify loneliness in a more nuanced way, which ingrains the core aspect of stigma in loneliness. Specifically, Chapter 6 presents a reconceptualisation of the loneliness Taxonomy defined by Kivran-Swaine et al. (2014) in which, when labelling loneliness self-disclosure, there is a need to include a "direct or indirect" disclosure label, to enable the nuanced understanding of loneliness which is not currently present in the loneliness text analysis literature.

7.5 Limitations

Several important limitations constrain this work and identify areas where future research might achieve greater methodological strength

1. **UK-centric Findings**: All the included studies focus on UK contexts, including practitioners working within UK services (Study 1), UK users of Kooth (Studies 2 and 4), and London residents (Study 3). This limits generalisability to countries with different welfare systems, healthcare structures, or cultural attitudes toward loneliness.

2. **Social Desirability Bias**: Self-reporting of loneliness may be underestimated due to the associated stigma. This is particularly relevant in Study 3, where questions about loneliness were presented alongside de-

privation and poverty questions, which may have triggered shame-based responses, preventing the honest disclosure of loneliness.

3. **Digital Platform Limitations**: Data collection was limited to users of specific digital platforms, including Kooth (Studies 2 and 4), Olio (Study 3), and Reddit (Study 4). This, therefore, excludes populations with limited digital access (typically older adults) or those who prefer face-to-face intervention services, potentially missing the most isolated individuals.

4. **Ethical Considerations Surrounding Digital Data**: The use of social media data (Study 4) raises questions about informed consent. While Reddit posts are publicly accessible, users may not expect their posts to be used for research purposes. This reflects broader unresolved issues in digital research ethics regarding what constitutes appropriate use of social media data and informed consent. An example of where researchers have not been mindful of the ethical considerations of using social media (specifically Reddit) data, in which (Lyons et al., 2024) collected data from a subreddit, which had a clear rule that all research requires approval of the moderators - this led to the retraction of Lyons et al. (2024)'s paper.

7.6 Future Work

This thesis demonstrates that loneliness is a serious and prevalent public health concern, with findings showing that stigma, and specifically stigmatised deprivation, creates barriers to direct disclosure, leading to indirect expressions of loneliness in therapeutic settings. Building on these insights, several future research directions emerge that could provide a more robust understanding of the lived experience of loneliness.

This thesis has identified that multiple data sources should be combined and evaluated together rather than in isolation. While challenging to achieve, there is potential to understand loneliness at scale by combining social media text data with granular loneliness scales to examine loneliness across user demographics using rigorous data collection methodologies. However, this has yet to be realised to a sufficient quality.

There should be a focused effort to create an effective, granularly labelled dataset of both direct and indirect expressions of loneliness, enabling nuanced analysis of loneliness. It should be noted that this approach to labelling data should be subject to change, as the way in which individuals discuss loneliness online or in therapeutic environments may change; the labelling approach must also reflect these changes, and, as identified in Chapter 3, the language used to express loneliness concerns can change based on the age of the individual. This labelling process can be designed based on the types of disclosure identified throughout the thesis. Chapter 3 illustrates the prevalence of indirect disclosure in therapeutic settings, while Chapter 5 highlights the importance of considering environmental, economic, and social factors that contribute to loneliness. Combining these approaches would enable future research to evaluate loneliness experiences more comprehensively, providing a clearer understanding of how loneliness manifests in people's lives.

As described in the literature review Chapter 2 subsection 2.4.2, there is still little work being undertaken to measure the stigma of loneliness, which warrants further exploration. While the Stigma of Loneliness Scale (SLS) was created by Ko et al. (2022), its uptake remains limited. The incorporation of the SLS with other loneliness measurement scales and questionnaires about environmental, economic, and social factors can offer further granular insight into loneliness. Specifically, it could be possible to link stigmatised experiences expressed in text to loneliness self-disclosure through the NLP methods, achieved through rigorous data labelling approaches, which will help connect these experiences. There is also the potential to incorporate the Adult SWAN-OM loneliness questions to identify specific concerns that align with loneliness, enabling targeted support within the context of digital mental health interventions.

7.6.1 Thesis Study Expansions

While the preceding opportunities for future work have emerged from the completion of the studies in this thesis and the comprehensive literature review, there are also opportunities to expand the work undertaken in this thesis to add additional rigour and robust insights.

Expanding Study 1 (Chapter 3)

The most pertinent point is the small number of practitioner interviews as part of Study 1 (Chapter 3), as a more significant number of practitioners could reinforce the identified experiences of loneliness, while the results would have greater rigour and potentially unveil further insights.

Expanding Study 3 (Chapter 5)

Study 3 could be expanded by incorporating a more robust set of questions relating to loneliness and stigma. While a subset of UCLA loneliness scale questions was asked as part of the survey in Study 3, a longer form loneliness scale (such as the 20-item Revised UCLA loneliness scale) may offer more nuanced insights into loneliness when related to deprivation. In combination with a scale measuring the perceived stigma of loneliness, it may also provide another avenue of investigation across populations, such as identifying the stigma of loneliness in relation to deprivation indices. A collection of responses from a broader population, rather than only those who engage in food sharing via Olio, as this may present a skewed distribution of those who need to use the food sharing app if they are deprived.

7.7 Concluding Remarks

Loneliness is something we are all perhaps destined to experience at some point in our lives, however fleeting. *A disconnect between the true and desired social experience.* Despite the prevalence of social outreach programmes and mental health interventions for loneliness, it continues to persist.

In writing this thesis, it has become apparent to me that loneliness is not just about being alone — in fact, it is very far from that. I believe that the insights I have gleaned from conducting this research suggest that loneliness is a **symptom of broader societal *failure***.

The biggest realisation from this thesis is the role of stigmatised experiences, which cause social shame, and the impact of these experiences on individuals and society. *Why should we feel stigma about such common concerns which are not the result of failings of our own?* As I have demonstrated, these stigmatised experiences, energy insecurity, food insecurity, and mental health concerns are only stigmatised because of our societal perceptions of them.

If we could all afford to live in accommodation of *appropriate standards*, earn enough money to *afford food and heat our homes*, and when we *do* struggle, be able to ask for help without internal or societal stigma, loneliness would be far less prevalent.

These basic conditions for human dignity are not too much to ask for.

Bibliography

Abplanalp, S. J., Green, M. F., Wynn, J. K., Eisenberger, N. I., Horan, W. P., Lee, J., McCleery, A., Miklowitz, D. J., Reddy, L. F., & Reavis, E. A. (2024). Using machine learning to understand social isolation and loneliness in schizophrenia, bipolar disorder, and the community. *Schizophrenia*, *10*(1), 88. https://doi.org/10.1038/s41537-024-00511-y

Akhter-Khan, S. C., & Au, R. (2020). Why Loneliness Interventions Are Unsuccessful: A Call for Precision Health. *Advances in geriatric medicine and research*, *2*(3), e200016. https://doi.org/10.20900/agmr20200016

Akkoca Gazioğlu, B. S., & Kamaşak, M. E. (2021). Effects of objects and image quality on melanoma classification using deep neural networks. *Biomedical Signal Processing and Control*, *67*, 102530. https://doi.org/10.1016/j.bspc.2021.102530

Allen, K.-A. (2020). Commentary: A Pilot Digital Intervention Targeting Loneliness in Youth Mental Health. *Frontiers in Psychiatry*, *10*, 959. https://doi.org/10.3389/fpsyt.2019.00959

Alonzo, A. A., & Reynolds, N. R. (1995). Stigma, HIV and AIDS: An exploration and elaboration of a stigma trajectory. *Social Science & Medicine (1982)*, *41*(3), 303–315. https://doi.org/10.1016/0277-9536(94)00384-6

Althoff, T., Clark, K., & Leskovec, J. (2016a). Natural Language Processing for Mental Health: Large Scale Discourse Analysis of Counseling Conversations. *Transactions of the Association for Computational Linguistics*, *4*. https://doi.org/10.1162/tacl_a_00111

Althoff, T., Clark, K., & Leskovec, J. (2016b). Large-scale Analysis of Counseling Conversations: An Application of Natural Language Processing to Mental Health. *Transactions of the Association for Computational Linguistics*, *4*, 463–476. https://doi.org/10.1162/tacl_a_00111

Altschul, D., Iveson, M., & Deary, I. J. (2021). Generational differences in loneliness and its psychological and sociodemographic predictors: An exploratory and confirmatory machine learning study. *Psychological Medicine*, *51*(6), 991–1000. https://doi.org/10.1017/S0033291719003933

Alvarez, C. V., Mirza, L., Das-Munshi, J., & Oswald, T. K. (2025). Social connection interventions and depression in young adults: A systematic review and meta-analysis. *Social Psychiatry and Psychiatric Epidemiology*, *60*(3), 549–562. https://doi.org/10.1007/s00127-024-02722-1

Andersen, M. M., Varga, S., & Folker, A. P. (2022). On the definition of stigma. *Journal of Evaluation in Clinical Practice*, *28*(5), 847–853. https://doi.org/10.1111/jep.13684

Andersson, L. (1985). Intervention against loneliness in a group of elderly women: An impact evaluation. *Social Science & Medicine (1982)*, *20*(4), 355–364. https://doi.org/10.1016/0277-9536(85)90010-3

Andrews, G. J., Gavin, N., Begley, S., & Brodie, D. (2003). Assisting friendships, combating loneliness: Users' views on a 'befriending' scheme. *Ageing & Society*, *23*(3), 349–362. https://doi.org/10.1017/S0144686X03001156

Andy, A. (2021). Understanding user communication around loneliness on online forums (B. Guidi, Ed.). *PLOS ONE*, *16*(9), e0257791. https://doi.org/10.1371/journal.pone.0257791

Arachchige, N., Sandanapitchai, P., Weerasinghe, R., & Isuri, A. (2021). Investigating Machine Learning & Natural Language Processing Techniques Applied for Predicting Depression Disorder from Online Support Forums: A Systematic Literature Review. *Information*, *12*(11), 444. https://doi.org/10.3390/info12110444

Arenas, D. J., Thomas, A., Wang, J., & DeLisser, H. M. (2019). A Systematic Review and Meta-analysis of Depression, Anxiety, and Sleep Disorders in US Adults with Food Insecurity. *Journal of General Internal Medicine*, *34*(12), 2874–2882. https://doi.org/10.1007/s11606-019-05202-4

Asher, S. R., Hymel, S., & Renshaw, P. D. (1984). Loneliness in Children. *Child Development*, *55*(4), 1456. https://doi.org/10.2307/1130015

Asher, S. R., & Wheeler, V. A. (1985). Children's loneliness: A comparison of rejected and neglected peer status. *Journal of Consulting and Clinical Psychology*, *53*(4), 500–505. https://doi.org/10.1037/0022-006X.53.4.500

Ashworth, M., Guerra, D., & Kordowicz, M. (2019). Individualised or Standardised Outcome Measures: A Co-habitation? *Administration and Policy in Mental Health and Mental Health Services Research*, *46*(4), 425–428. https://doi.org/10.1007/s10488-019-00928-z

Astell-Burt, T., Hartig, T., Putra, I. G. N. E., Walsan, R., Dendup, T., & Feng, X. (2022). Green space and loneliness: A systematic review with theoretical and methodological guidance for future research. *Science of The Total Environment*, *847*, 157521. https://doi.org/10.1016/j.scitotenv.2022.157521

Asudani, D. S., Nagwani, N. K., & Singh, P. (2023). Impact of word embedding models on text analytics in deep learning environment: A review. *Artificial Intelligence Review*, *56*(9), 10345–10425. https://doi.org/10.1007/s10462-023-10419-1

Badal, V. D., Graham, S. A., Depp, C. A., Shinkawa, K., Yamada, Y., Palinkas, L. A., Kim, H.-C., Jeste, D. V., & Lee, E. E. (2021). Prediction of Loneliness in Older Adults Using Natural Language Processing: Exploring Sex Differences in Speech. *The American Journal of Geriatric Psychiatry*, *29*(8), 853–866. https://doi.org/10.1016/j.jagp.2020.09.009

Badal, V. D., Lee, E. E., Daly, R., Parrish, E. M., Kim, H.-C., Jeste, D. V., & Depp, C. A. (2022). Dynamics of Loneliness Among Older Adults During the COVID-19 Pandemic: Pilot Study of Ecological Momentary Assessment With Network Analysis. *Frontiers in Digital Health*, *4*. https://doi.org/10.3389/fdgth.2022.814179

Badal, V. D., Nebeker, C., Shinkawa, K., Yamada, Y., Rentscher, K. E., Kim, H.-C., & Lee, E. E. (2021). Do Words Matter? Detecting Social Isolation and Loneliness in Older Adults Using Natural Language Processing. *Frontiers in Psychiatry*, *12*, 728732. https://doi.org/10.3389/fpsyt.2021.728732

Balcombe, L., & De Leo, D. (2023). Evaluation of the Use of Digital Mental Health Platforms and Interventions: Scoping Review. *International Journal of Environmental Research and Public Health*, *20*(1), 362. https://doi.org/10.3390/ijerph20010362

Balki, E., Hayes, N., & Holland, C. (2022). Effectiveness of Technology Interventions in Addressing Social Isolation, Connectedness, and Loneliness in Older Adults: Systematic Umbrella Review. *JMIR Aging*, *5*(4), e40125. https://doi.org/10.2196/40125

Banks, J., & Xu, X. (2020). The Mental Health Effects of the First Two Months of Lockdown during the COVID-19 Pandemic in the UK*. *Fiscal Studies*, *41*(3), 685–708. https://doi.org/10.1111/1475-5890.12239

Barreto, M., Van Breen, J., Victor, C., Hammond, C., Eccles, A., Richins, M. T., & Qualter, P. (2022). Exploring the nature and variation of the stigma associated with loneliness. *Journal of Social and Personal Relationships*, *39*(9), 2658–2679. https://doi.org/10.1177/02654075221087190

Barreto, M., Victor, C., Hammond, C., Eccles, A., Richins, M. T., & Qualter, P. (2021). Loneliness around the world: Age, gender, and cultural differences in loneliness. *Personality and Individual Differences*, *169*, 110066. https://doi.org/10.1016/j.paid.2020.110066

Barry, M. J. (1962). Depression, shame, loneliness, and the psychiatrist's position. *American Journal of Psychotherapy*, *16*, 580–590. https://doi.org/10.1176/appi.psychotherapy.1962.16.4.580

Bartrés-Faz, D., Macià, D., Cattaneo, G., Borràs, R., Tarrero, C., Solana, J., Tormos, J. M., & Pascual-Leone, A. (2021). The paradoxical effect of COVID-19 outbreak on loneliness. *BJPsych Open*, *7*(1), e30. https://doi.org/10.1192/bjo.2020.163

Beller, J., & Wagner, A. (2020). Loneliness and Health: The Moderating Effect of Cross-Cultural Individualism/Collectivism. *Journal of Aging and Health*, *32*(10), 1516–1527. https://doi.org/10.1177/0898264320943336

Bergefurt, L., Kemperman, A., Van Den Berg, P., Borgers, A., Van Der Waerden, P., Oosterhuis, G., & Hommel, M. (2019). Loneliness and Life Satisfaction Explained by Public-Space Use and Mobility Patterns. *International Journal of Environmental Research and Public Health*, *16*(21), 4282. https://doi.org/10.3390/ijerph16214282

Bianchi, F., Terragni, S., Hovy, D., Nozza, D., & Fersini, E. (2021, February 4). *Cross-lingual Contextualized Topic Models with Zero-shot Learning.* arXiv: 2004.07737 [cs]. Retrieved January 29, 2023, from http://arxiv.org/abs/2004.07737

Birken, M., Chipp, B., Shah, P., Olive, R. R., Nyikavaranda, P., Hardy, J., Chhapia, A., Barber, N., Lee, S., Pearce, E., Lloyd-Evans, B., Perkins, R., McDaid, D., Stefanidou, T., Shafran, R., Pitman, A., & Johnson, S. (2023). Exploring the experiences of loneliness in adults with mental health problems: A participatory qualitative interview study. *PLOS ONE*, *18*(3), e0280946. https://doi.org/10.1371/journal.pone.0280946

Blais, M. A., Lenderking, W. R., Baer, L., deLorell, A., Peets, K., Leahy, L., & Burns, C. (1999). Development and Initial Validation of a Brief Mental Health Outcome Measure. *Journal of Personality Assessment*, *73*(3), 359–373. https://doi.org/10.1207/S15327752JPA7303_5

Blei, D. M., & Lafferty, J. D. (2006). Dynamic topic models. *Proceedings of the 23rd International Conference on Machine Learning - ICML '06*, 113–120. https://doi.org/10.1145/1143844.1143859

Borghouts, J., Eikey, E., Mark, G., Leon, C. D., Schueller, S. M., Schneider, M., Stadnick, N., Zheng, K., Mukamel, D., & Sorkin, D. H. (2021). Barriers to and Facilitators of User Engagement With Digital Mental Health Interventions: Systematic Review. *Journal of Medical Internet Research*, *23*(3), e24387. https://doi.org/10.2196/24387

Braciszewski, J. M. (2021). Digital Technology for Suicide Prevention. *Advances in Psychiatry and Behavioral Health*, *1*(1), 53–65. https://doi.org/10.1016/j.ypsc.2021.05.008

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, *3*(2), 77–101. https://doi.org/10.1191/1478088706qp063oa

Bruehlman-Senecal, E., Hook, C. J., Pfeifer, J. H., FitzGerald, C., Davis, B., Delucchi, K. L., Haritatos, J., & Ramo, D. E. (2020). Smartphone App to Address Loneliness Among College Students: Pilot Randomized Controlled Trial. *JMIR Mental Health*, *7*(10), e21496. https://doi.org/10.2196/21496

Brunner, K.-M., Spitzer, M., & Christanell, A. (2012). Experiencing fuel poverty. Coping strategies of low-income households in Vienna/Austria. *Energy Policy*, *49*, 53–59. https://doi.org/10.1016/j.enpol.2011.11.076

Bu, F., Steptoe, A., & Fancourt, D. (2020). Loneliness during a strict lockdown: Trajectories and predictors during the COVID-19 pandemic in 38,217 United Kingdom adults. *Social Science & Medicine*, *265*, 113521. https://doi.org/10.1016/j.socscimed.2020.113521

Burris, M., Kihlstrom, L., Arce, K. S., Prendergast, K., Dobbins, J., McGrath, E., Renda, A., Shannon, E., Cordier, T., Song, Y., & Himmelgreen, D. (2021). Food Insecurity, Loneliness, and Social Support among Older Adults. *Journal of Hunger & Environmental Nutrition*, *16*(1), 29–44. https://doi.org/10.1080/19320248.2019.1595253

Cacioppo, J. T., & Cacioppo, S. (2012). The Phenotype of Loneliness. *The European journal of developmental psychology*, *9*(4), 446–452. https://doi.org/10.1080/17405629.2012.690510

Cacioppo, J. T., Hawkley, L. C., & Thisted, R. A. (2010). Perceived social isolation makes me sad: 5-year cross-lagged analyses of loneliness and depressive symptomatology in the Chicago Health, Aging, and Social Relations Study. *Psychology and Aging*, *25*(2), 453–463. https://doi.org/10.1037/a0017216

Cacioppo, J. T., & Patrick, W. (2008). *Loneliness: Human nature and the need for social connection.* W. W. Norton & Company.

Caple, V., Maude, P., Walter, R., & Ross, A. (2023). An exploration of loneliness experienced by people living with mental illness and the impact on their recovery journey: An integrative review. *Journal of Psychiatric* *and Mental Health Nursing*, *30*(6), 1170–1191. https://doi.org/10.1111/jpm.12945

Cattan, M., Kime, N., & Bagnall, A.-M. (2011). The use of telephone befriending in low level support for socially isolated older people–an evaluation. *Health & Social Care in the Community*, *19*(2), 198–206. https://doi.org/10.1111/j.1365-2524.2010.00967.x

Cattan, M., Newell, C., Bond, J., & White, M. (2003). Alleviating Social Isolation and Loneliness among Older People. *International Journal of Mental Health Promotion*, *5*(3), 20–30. https://doi.org/10.1080/14623730.2003.9721909

Chancellor, S., & De Choudhury, M. (2020). Methods in predictive techniques for mental health status on social media: A critical review. *npj Digital Medicine*, *3*(1), 1–11. https://doi.org/10.1038/s41746-020-0233-7

Chatterjee, S. S., Barikar C, M., & Mukherjee, A. (2020). Impact of COVID-19 pandemic on pre-existing mental health problems. *Asian Journal of Psychiatry*, *51*, 102071. https://doi.org/10.1016/j.ajp.2020.102071

Cheetham, M., Moffatt, S., Addison, M., & Wiseman, A. (2019). Impact of Universal Credit in North East England: A qualitative study of claimants and support staff. *BMJ Open*, *9*(7), e029611. https://doi.org/10.1136/bmjopen-2019-029611

Chiang, K.-J., Chu, H., Chang, H.-J., Chung, M.-H., Chen, C.-H., Chiou, H.-Y., & Chou, K.-R. (2010). The effects of reminiscence therapy on psychological well-being, depression, and loneliness among the institutionalized aged. *International Journal of Geriatric Psychiatry*, *25*(4), 380–388. https://doi.org/10.1002/gps.2350

Choi, S., Kang, H., Shin, J., Chu, S. H., & Choi, J. (2025). Ecological Momentary Assessment to Measure Social Connectedness in Older Adults: Integrative Review. *Journal of Medical Internet Research*, *27*(1), e66324. https://doi.org/10.2196/66324

Choudhury, M. D., Gamon, M., Counts, S., & Horvitz, E. (2013). Predicting Depression via Social Media. *Proceedings of the International AAAI Conference on Web and Social Media*, *7*(1), 128–137. https://doi.org/10.1609/icwsm.v7i1.14432

Clark, K., Khandelwal, U., Levy, O., & Manning, C. D. (2019, August). What Does BERT Look at? An Analysis of BERT's Attention. In T. Linzen, G. Chrupała, Y. Belinkov, & D. Hupkes (Eds.), *Proceedings of the 2019 ACL Workshop BlackboxNLP: Analyzing and Interpreting Neural Networks for NLP* (pp. 276–286). Association for Computational Linguistics. https://doi.org/10.18653/v1/W19-4828

Clarke, A., Friede, T., Putz, R., Ashdown, J., Martin, S., Blake, A., Adi, Y., Parkinson, J., Flynn, P., Platt, S., & Stewart-Brown, S. (2011). Warwick-Edinburgh Mental Well-being Scale (WEMWBS): Validated for teenage school students in England and Scotland. A mixed methods assessment. *BMC Public Health*, *11*(1), 487. https://doi.org/10.1186/1471-2458-11-487

Cook, B. L., Progovac, A. M., Chen, P., Mullin, B., Hou, S., & Baca-Garcia, E. (2016). Novel Use of Natural Language Processing (NLP) to Predict Suicidal Ideation and Psychiatric Symptoms in a Text-Based Mental

Health Intervention in Madrid. *Computational and Mathematical Methods in Medicine*, *2016*, 1–8. https://doi.org/10.1155/2016/8708434

Cooper, F. (2024). 'Solitude is not thrust upon any lovable person': Loneliness, shame and the problem (of) personality. *Journal of Psychosocial Studies*, *17*(1), 28–45. https://doi.org/10.1332/14786737y2023d000000004

Coppersmith, G., Dredze, M., & Harman, C. (2014, June). Quantifying Mental Health Signals in Twitter. In P. Resnik, R. Resnik, & M. Mitchell (Eds.), *Proceedings of the Workshop on Computational Linguistics and Clinical Psychology: From Linguistic Signal to Clinical Reality* (pp. 51–60). Association for Computational Linguistics. https://doi.org/10.3115/v1/W14-3207

Coppersmith, G., Leary, R., Crutchley, P., & Fine, A. (2018). Natural Language Processing of Social Media as Screening for Suicide Risk. *Biomedical Informatics Insights*, *10*, 1–11. https://doi.org/10.1177/1178222618792860

Costello, M. A., Nagel, A. G., Hunt, G. L., Rivens, A. J., Hazelwood, O. A., Pettit, C., & Allen, J. P. (2022). Facilitating connection to enhance college student well-being: Evaluation of an experiential group program. *American Journal of Community Psychology*, *70*(3–4), 314–326. https://doi.org/10.1002/ajcp.12601

Crocker, J. (1999). Social Stigma and Self-Esteem: Situational Construction of Self-Worth. *Journal of Experimental Social Psychology*, *35*(1), 89–107. https://doi.org/10.1006/jesp.1998.1369

Cross, J. L., Choma, M. A., & Onofrey, J. A. (2024). Bias in medical AI: Implications for clinical decision-making. *PLOS Digital Health*, *3*(11), e0000651. https://doi.org/10.1371/journal.pdig.0000651

Dahlberg, K. (2007). The enigmatic phenomenon of loneliness. *International Journal of Qualitative Studies on Health and Well-being*, *2*(4), 195–207. https://doi.org/10.1080/17482620701626117

Davis, H. A., Kells, M., Todorov, S., Kosmas, J., & Wildes, J. E. (2023). Comorbid eating, depressive, and anxiety psychopathology is associated with elevated shame in women with food insecurity. *International Journal of Eating Disorders*, *56*(6), 1087–1097. https://doi.org/10.1002/eat.23913

de Jong Gierveld, J., & Havens, B. (2004). Cross-national comparisons of social isolation and loneliness: Introduction and overview. *Canadian Journal on Aging = La Revue Canadienne Du Vieillissement*, *23*(2), 109–113. https://doi.org/10.1353/cja.2004.0021

De Jong Gierveld, J., & Van Tilburg, T. (2010). The De Jong Gierveld short scales for emotional and social loneliness: Tested on data from 7 countries in the UN generations and gender surveys. *European Journal of Ageing*, *7*(2), 121–130. https://doi.org/10.1007/s10433-010-0144-6

de Jong-Gierveld, J. (1987). Developing and testing a model of loneliness. *Journal of personality and social psychology*, *53*(1), 119.

De Ossorno Garcia, S., Edbrooke-Childs, J., Salhi, L., Ruby, F., Sefi, A., & Jacob, J. (2022, June 8). *"Examining concurrent validity and item selection of the Wants and Needs Outcome Measure (SWAN-OM) in a web-based therapy service" (Preprint)* (preprint). JMIR Mental Health. https://doi.org/10.2196/preprints.40122

De Ossorno Garcia, S., Salhi, L., Sefi, A., & Hanley, T. (2021). The Session Wants and Need Outcome Measure: The Development of a Brief Outcome Measure for Single-Sessions of Web-Based Support. *Frontiers in Psychology*, *12*, 748145. https://doi.org/10.3389/fpsyg.2021.748145

DeepSeek-AI, Guo, D., Yang, D., Zhang, H., Song, J., Zhang, R., Xu, R., Zhu, Q., Ma, S., Wang, P., Bi, X., Zhang, X., Yu, X., Wu, Y., Wu, Z. F., Gou, Z., Shao, Z., Li, Z., Gao, Z., ... Zhang, Z. (2025, January 22). *DeepSeek-R1: Incentivizing Reasoning Capability in LLMs via Reinforcement Learning*. arXiv: 2501.12948 [cs]. https://doi.org/10.48550/arXiv.2501.12948

Delbosc, A. (2012). The role of well-being in transport policy. *Transport Policy*, *23*, 25–33. https://doi.org/10.1016/j.tranpol.2012.06.005

Denner, S., & Reeves, S. (1997). Single session assessment and therapy for new referrals to CMHTS. *Journal of Mental Health*, *6*(3), 275–280. https://doi.org/10.1080/09638239718806

Department for Digital, Culture, Media and Sport. (2018). *A connected society: A strategy for tackling loneliness* (Policy Paper). Department for Digital, Culture, Media and Sport. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/936725/6.4882_DCMS_Loneliness_Strategy_web_Update_V2.pdf

Department for Digital, Culture, Media and Sport. (2023, March). *Tackling Loneliness annual report March 2023: The fourth year* (Policy Paper). Department for Digital, Culture, Media and Sport. https://www.gov.uk/government/publications/loneliness-annual-report-the-fourth-year

Department for Media Culture and Sport. (2023, January). *Tackling loneliness evidence review: Main report* (Independent report). https://www.gov.uk/government/publications/tackling-loneliness-evidence-review/tackling-loneliness-evidence-review-full-report

Department for Work and Pensions & Government, U. K. (2025, June 15). *Further details on welfare reforms published ahead of Second Reading.* https://www.gov.uk/government/news/further-details-on-welfare-reforms-published-ahead-of-second-reading

Dettmann, L. M., Adams, S., & Taylor, G. (2022). Investigating the prevalence of anxiety and depression during the first COVID-19 lockdown in the United Kingdom: Systematic review and meta-analyses. *British Journal of Clinical Psychology*, *61*(3), 757–780. https://doi.org/10.1111/bjc.12360

Devlin, J., Chang, M.-W., Lee, K., & Toutanova, K. (2019–June 7). BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. *Proceedings of NAACL-HLT 2019*, 16. https://doi.org/10.48550/arXiv.1810.04805

DiTommaso, E., & Spinner, B. (1993). The development and initial validation of the Social and Emotional Loneliness Scale for Adults (SELSA). *Personality and Individual Differences*, *14*(1), 127–134. https://doi.org/10.1016/0191-8869(93)90182-3

Dobarrio-Sanz, I., Ruiz-González, C., Fernández-Sola, C., Roman, P., Granero-Molina, J., & Hernández-Padilla, J. M. (2021). Healthcare Professionals' Perceptions of Loneliness amongst Older Adults: A Qualitative

Study. *International Journal of Environmental Research and Public Health*, *18*(22), 12071. https://doi.org/10.3390/ijerph182212071

Dolan, E., Goulding, J., Marshall, H., Smith, G., Long, G., & Tata, L. J. (2023). Assessing the value of integrating national longitudinal shopping data into respiratory disease forecasting models. *Nature Communications*, *14*(1), 7258. https://doi.org/10.1038/s41467-023-42776-4

Doryab, A., Villalba, D. K., Chikersal, P., Dutcher, J. M., Tumminia, M., Liu, X., Cohen, S., Creswell, K., Mankoff, J., Creswell, J. D., & Dey, A. K. (2019). Identifying Behavioral Phenotypes of Loneliness and Social Isolation with Passive Sensing: Statistical Analysis, Data Mining and Machine Learning of Smartphone and Fitbit Data. *JMIR mHealth and uHealth*, *7*(7), e13209. https://doi.org/10.2196/13209

Doshi-Velez, F., & Kim, B. (2017, March 2). *Towards A Rigorous Science of Interpretable Machine Learning*. arXiv: 1702.08608 [stat]. https://doi.org/10.48550/arXiv.1702.08608

Dougherty, D. S., Rick, J. M., & Moore, P. (2017). Unemployment and social class stigmas. *Journal of Applied Communication Research*, *45*(5), 495–516. https://doi.org/10.1080/00909882.2017.1382708

Dryden, W. (2020a). Single-Session One-At-A-Time Therapy: A Personal Approach. *Australian and New Zealand Journal of Family Therapy*, *41*(3), 283–301. https://doi.org/10.1002/anzf.1424

Dryden, W. (2020b, December 18). *What is Single-Session Therapy?* Windy Dryden. Retrieved January 18, 2024, from https://www.windydryden.com/post/what-is-single-session-therapy

Dworschak, C., Heim, E., Tröster, A., Grunder, C., & Maercker, A. (2024). Feasibility, acceptability, and preliminary efficacy of an internet-based CBT intervention for loneliness in older adults: A pilot RCT. *Journal of Affective Disorders Reports*, *15*, 100692. https://doi.org/10.1016/j.jadr.2023.100692

Ejlskov, L., Wulff, J., Bøggild, H., Kuh, D., & Stafford, M. (2018). Assessing the relative importance of correlates of loneliness in later life. Gaining insight using recursive partitioning. *Aging & Mental Health*, *22*(11), 1486–1493. https://doi.org/10.1080/13607863.2017.1370690

Elgar, F. J., Pickett, W., Pförtner, T.-K., Gariépy, G., Gordon, D., Georgiades, K., Davison, C., Hammami, N., MacNeil, A. H., Azevedo Da Silva, M., & Melgar-Quiñonez, H. R. (2021). Relative food insecurity, mental health and wellbeing in 160 countries. *Social Science & Medicine*, *268*, 113556. https://doi.org/10.1016/j.socscimed.2020.113556

Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., & Thrun, S. (2017). Dermatologist-level classification of skin cancer with deep neural networks. *Nature*, *542*(7639), 115–118. https://doi.org/10.1038/nature21056

Evans, C., Connell, J., Barkham, M., Margison, F., McGrath, G., Mellor-Clark, J., & Audin, K. (2002). Towards a standardised brief outcome measure: Psychometric properties and utility of the CORE–OM. *British Journal of Psychiatry*, *180*(1), 51–60. https://doi.org/10.1192/bjp.180.1.51

Fan, W., Fan, J., Yu, J., Zhang, M., Du, Q., Tong, L., & Fan, W. ((2025). Loneliness Detection from Social Media: A Text Analytics Approach. https://doi.org/10.24251/HICSS.2025.454

Fan, Z., Shi, X., Leng, J., Cui, D., & Li, D. (2025). The Impact of Stigma of Loneliness on Psychological Distress in Older Adults: The Chain Mediating Effect. *Psychology Research and Behavior Management*, *18*, 25–38. https://doi.org/10.2147/PRBM.S494430

Fan, Z., Shi, X., Luo, Y., Chen, H., & Wen, H. (2025). The Chinese version of the stigma of loneliness scale in people with chronic diseases: An assessment of psychometric characteristics. *BMC Public Health*, *25*(1), 1619. https://doi.org/10.1186/s12889-025-22743-y

Fan, Z., Shi, X., Yang, S., Sun, Y., & Chen, R. (2024). Reliability and validity evaluation of the stigma of loneliness scale in Chinese college students. *BMC Public Health*, *24*, 238. https://doi.org/10.1186/s12889-024-17738-0

Fardghassemi, S., & Joffe, H. (2022). The causes of loneliness: The perspective of young adults in London's most deprived areas (M. Vall-llosera Camps, Ed.). *PLOS ONE*, *17*(4), e0264638. https://doi.org/10.1371/journal.pone.0264638

Farrell, A. H., Vitoroulis, I., Eriksson, M., & Vaillancourt, T. (2023). Loneliness and Well-Being in Children and Adolescents during the COVID-19 Pandemic: A Systematic Review. *Children*, *10*(2), 279. https://doi.org/10.3390/children10020279

Fisher, A., Rudin, C., & Dominici, F. (2019). All Models are Wrong, but Many are Useful: Learning a Variable's Importance by Studying an Entire Class of Prediction Models Simultaneously. *Journal of machine learning research : JMLR*, *20*, 177. Retrieved September 23, 2024, from https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8323609/

Fittipaldi, S., Teckentrup, V., Rosická, A. M., Lawlor, B., & Gillan, C. M. (2024). The relationship between loneliness, depression and cognition: Evidence from smartphone-based cross-sectional and ecological momentary assessment. *Alzheimer's & Dementia*, *20*(S3), e089194. https://doi.org/10.1002/alz.089194

for National Statistics, O. (2021). *Coronavirus and the social impacts on Great Britain*. https://www.ons.gov.uk/peoplepopulationandcommunity/healthandsocialcare/healthandwellbeing/datasets/coronavirusandthesocialimpactsong

for Work and Pensions, D. (2025, July 23). *Spring Statement 2025 health and disability benefit reforms – Equality Analysis* (Policy Summary). Retrieved September 5, 2025, from https://www.gov.uk/government/consultations/pathways-to-work-reforming-benefits-and-support-to-get-britain-working-green-paper/spring-statement-2025-health-and-disability-benefit-reforms-equality-analysis

Garg, M., Saxena, C., Samanta, D., & Dorr, B. J. (2023). LonXplain: Lonesomeness as a Consequence of Mental Disturbance in Reddit Posts. In E. Métais, F. Meziane, V. Sugumaran, W. Manning, & S. Reiff-Marganiec (Eds.), *Natural Language Processing and Information Systems* (pp. 379–390). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-35320-8_27

Gasull-Molinera, V., Khan, K. S., Núñez Núñez, M., & Kouiti, M. (2024). The impact of loneliness on mental and physical health outcomes: An umbrella review. *Medicina de Familia. SEMERGEN*, *50*(6). https://doi.org/10.1016/j.semerg.2024.102261

Geirhos, R., Jacobsen, J.-H., Michaelis, C., Zemel, R., Brendel, W., Bethge, M., & Wichmann, F. A. (2020). Shortcut learning in deep neural networks. *Nature Machine Intelligence*, *2*(11), 665–673. https://doi.org/10.1038/s42256-020-00257-z

Geirhos, R., Rubisch, P., Michaelis, C., Bethge, M., Wichmann, F. A., & Brendel, W. (2022, November 9). *ImageNet-trained CNNs are biased towards texture; increasing shape bias improves accuracy and robustness.* arXiv: 1811.12231 [cs]. https://doi.org/10.48550/arXiv.1811.12231

Gerino, E., Rollè, L., Sechi, C., & Brustia, P. (2017). Loneliness, Resilience, Mental Health, and Quality of Life in Old Age: A Structural Equation Model. *Frontiers in Psychology*, *8*. https://doi.org/10.3389/fpsyg.2017.02003

Ghenţa, M., & Matei, A. (2025). Policy Recommendations to Address Loneliness in Later Life. In M. Aartsen, I. Precupetu, & B. Suanet (Eds.), *Macro Social Influences on Loneliness in Later Life: Towards a Better Understanding of the Loneliness Paradox in Europe* (pp. 299–320). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-94565-6_13

Gianfrancesco, M. A., Tamang, S., Yazdany, J., & Schmajuk, G. (2018). Potential Biases in Machine Learning Algorithms Using Electronic Health Record Data. *JAMA internal medicine*, *178*(11), 1544–1547. https://doi.org/10.1001/jamainternmed.2018.3763

Gilbody, S., Littlewood, E., McMillan, D., Atha, L., Bailey, D., Baird, K., Brady, S., Burke, L., Chew-Graham, C. A., Coventry, P., Crosland, S., Fairhurst, C., Henry, A., Hollingsworth, K., Newbronner, E., Ryde, E., Shearsmith, L., Wang, H.-I., Webster, J., … Ekers, D. (2024). Behavioural activation to mitigate the psychological impacts of COVID-19 restrictions on older people in England and Wales (BASIL+): A pragmatic randomised controlled trial. *The Lancet Healthy Longevity*, *5*(2), e97–e107. https://doi.org/10.1016/S2666-7568(23)00238-6

Gkotsis, G., Oellrich, A., Velupillai, S., Liakata, M., Hubbard, T. J. P., Dobson, R. J. B., & Dutta, R. (2017). Characterisation of mental health conditions in social media using Informed Deep Learning. *Scientific Reports*, *7*(1), 45141. https://doi.org/10.1038/srep45141

Goffman, E. (1963). *Stigma: Notes on the management of spoiled identity.* Penguin Books.

Goldman, N., Khanna, D., El Asmar, M. L., Qualter, P., & El-Osta, A. (2024). Addressing loneliness and social isolation in 52 countries: A scoping review of National policies. *BMC Public Health*, *24*(1), 1207. https://doi.org/10.1186/s12889-024-18370-8

Goodman, R. (1997). The Strengths and Difficulties Questionnaire: A Research Note. *Journal of Child Psychology and Psychiatry*, *38*(5), 581–586. https://doi.org/10.1111/j.1469-7610.1997.tb01545.x

Gorczynski, P., & Fasoli, F. (2022). Loneliness in sexual minority and heterosexual individuals: A comparative meta-analysis. *Journal of Gay & Lesbian Mental Health*, *26*(2), 112–129. https://doi.org/10.1080/19359705.2021.1957742

Gordy, A., Luo, H. H. W., Sidline, M., & Brownlee, K. (2022). The Missing Measure of Loneliness: A Case for Including Neededness in Loneliness Scales. *International Journal of Environmental Research and Public Health*, *19*(1), 429. https://doi.org/10.3390/ijerph19010429

Greater London Authority. (2022, October 31). *Survey of Londoners 2021-22* (Headline findings). Mayor of London. https://www.data.gov.uk/dataset/e0380796-00b3-43c0-80a8-5721249bb84b/survey-of-londoners-2021-22

Guntuku, S. C., Schneider, R., Pelullo, A., Young, J., Wong, V., Ungar, L., Polsky, D., Volpp, K. G., & Merchant, R. (2019). Studying expressions of loneliness in individuals using twitter: An observational study. *BMJ Open*, *9*(11), e030355. https://doi.org/10.1136/bmjopen-2019-030355

Guo, Z., Lai, A., Thygesen, J. H., Farrington, J., Keen, T., & Li, K. (2024). Large Language Models for Mental Health Applications: Systematic Review. *JMIR Mental Health*, *11*, e57400. https://doi.org/10.2196/57400

Han, D., & Han, M. (2023). *@software{unsloth, author = {Daniel Han, Michael Han and Unsloth team}, title = {Unsloth}, url = {http://github.com/unslothai/unsloth}, year = {2023} }*. http://github.com/unslothai/unsloth

Harker Steele, A. J., & Bergstrom, J. C. (2021). "Brr! It's cold in here" measures of household energy insecurity for the United States. *Energy Research & Social Science*, *72*, 101863. https://doi.org/10.1016/j.erss.2020.101863

Hawkley, L. C. (2022). Loneliness and health. *Nature Reviews Disease Primers*, *8*(1), 22. https://doi.org/10.1038/s41572-022-00355-9

Hawkley, L. C., & Cacioppo, J. T. (2010). Loneliness Matters: A Theoretical and Empirical Review of Consequences and Mechanisms. *Annals of Behavioral Medicine*, *40*(2), 218–227. https://doi.org/10.1007/s12160-010-9210-8

Hays, R. D., & DiMatteo, M. R. (1987). A short-form measure of loneliness. *Journal of Personality Assessment*, *51*(1), 69–81. https://doi.org/10.1207/s15327752jpa5101_6

Hennink, M., & Kaiser, B. N. (2022). Sample sizes for saturation in qualitative research: A systematic review of empirical tests. *Social Science & Medicine (1982)*, *292*, 114523. https://doi.org/10.1016/j.socscimed.2021.114523

Henseke, G., & Schoon, I. (2025). Revisiting the Mental Health Impact of COVID-19 on Young Adults in the UK: Long-Term Trends, Temporary Setbacks, and Recovery. *Social Indicators Research*. https://doi.org/10.1007/s11205-025-03616-8

Hernández, D. (2016). Understanding 'energy insecurity' and why it matters to health. *Social Science & Medicine*, *167*, 1–10. https://doi.org/10.1016/j.socscimed.2016.08.029

Hernández, D., & Siegel, E. (2019). Energy insecurity and its ill health effects: A community perspective on the energy-health nexus in New York City. *Energy Research & Social Science*, *47*, 78–83. https://doi.org/10.1016/j.erss.2018.08.011

Heu, L. C., Hansen, N., Zomeren, M., Levy, A., Ivanova, T. T., Gangadhar, A., & Radwan, M. (2021). Loneliness across cultures with different levels of social embeddedness: A qualitative study. *Personal Relationships*, *28*(2), 379–405. https://doi.org/10.1111/pere.12367

Hickin, N., Käll, A., Shafran, R., Sutcliffe, S., Manzotti, G., & Langan, D. (2021). The effectiveness of psychological interventions for loneliness: A systematic review and meta-analysis. *Clinical Psychology Review*, *88*, 102066. https://doi.org/10.1016/j.cpr.2021.102066

Hinshaw, S. P. (2007). *The mark of shame: Stigma of mental illness and an agenda for change*. Oxford University Press.

Hirschberg, J., & Manning, C. D. (2015). Advances in natural language processing. *ARTIFICIAL INTELLIGENCE*, *349*(6245), 7. https://doi.org/10.1126/science.aaa8685

Hogerwerf, L. J. W., & Suanet, B. (2025). Breaking the Silence on Loneliness in Society: Emerging Adults' Experiences With the Taboo and Stigma of Loneliness. *Emerging Adulthood*, *13*(4), 891–906. https://doi.org/10.1177/21676968251339224

Holding, E., Blank, L., Crowder, M., Ferrari, E., & Goyder, E. (2020). Exploring the relationship between housing concerns, mental health and wellbeing: A qualitative study of social housing tenants. *Journal of Public Health*, *42*(3), e231–e238. https://doi.org/10.1093/pubmed/fdz076

Honary, M., Fisher, N. R., McNaney, R., & Lobban, F. (2018). A Web-Based Intervention for Relatives of People Experiencing Psychosis or Bipolar Disorder: Design Study Using a User-Centered Approach. *JMIR Mental Health*, *5*(4), e11473. https://doi.org/10.2196/11473

Hoyt, M. F., Bobele, M., Slive, A., Young, J., & Talmon, M. (2018). Single-session/one-at-a-time walk-in therapy. In *Single-session therapy by walk-in or appointment: Administrative, clinical, and supervisory aspects of one-at-a-time services.* (pp. 3–24). Routledge/Taylor & Francis Group. https://doi.org/10.4324/9781351112437-1

Hua, Y., Liu, F., Yang, K., Li, Z., Na, H., Sheu, Y.-h., Zhou, P., Moran, L. V., Ananiadou, S., Clifton, D. A., Beam, A., & Torous, J. (2025, July 11). *Large Language Models in Mental Health Care: A Scoping Review*. arXiv: 2401.02984 [cs]. https://doi.org/10.48550/arXiv.2401.02984

Hughes, M. E., Waite, L. J., Hawkley, L. C., & Cacioppo, J. T. (2004). A Short Scale for Measuring Loneliness in Large Surveys: Results From Two Population-Based Studies. *Research on Aging*, *26*(6), 655–672. https://doi.org/10.1177/0164027504268574

Hymmen, P., Stalker, C. A., & Cait, C.-A. (2013). The case for single-session therapy: Does the empirical evidence support the increased prevalence of this service delivery model? *Journal of Mental Health*, *22*(1), 60–71. https://doi.org/10.3109/09638237.2012.670880

Ibrahim, M. (2012). THEMATIC ANALYSIS: A CRITICAL REVIEW OF ITS PROCESS AND EVALUATION. *1*(1).

Imwinkelried, M., Seewer, N., & Krieger, T. (2025). Psychological interventions for loneliness: A narrative review of recent findings and suggestions for future research. *Current Opinion in Behavioral Sciences*, *65*, 101586. https://doi.org/10.1016/j.cobeha.2025.101586

Iorfino, F., Cross, S. P., Davenport, T., Carpenter, J. S., Scott, E., Shiran, S., & Hickie, I. B. (2019). A Digital Platform Designed for Youth Mental Health Services to Deliver Personalized and Measurement-Based Care. *Frontiers in Psychiatry*, *10*. https://doi.org/10.3389/fpsyt.2019.00595

Jackson, R. G., Patel, R., Jayatilleke, N., Kolliakou, A., Ball, M., Gorrell, G., Roberts, A., Dobson, R. J., & Stewart, R. (2017). Natural language processing to extract symptoms of severe mental illness from clinical text: The Clinical Record Interactive Search Comprehensive Data Extraction (CRIS-CODE) project. *BMJ Open*, *7*(1), e012012. https://doi.org/10.1136/bmjopen-2016-012012

Jaidka, K., Giorgi, S., Schwartz, H. A., Kern, M. L., Ungar, L. H., & Eichstaedt, J. C. (2020). Estimating geographic subjective well-being from Twitter: A comparison of dictionary and data-driven language methods. *Proceedings of the National Academy of Sciences*, *117*(19), 10165–10171. https://doi.org/10.1073/pnas.1906364117

Janizek, J., Sturmfels, P., & Lee, S.-I. (2021). Explaining Explanations: Axiomatic Feature Interactions for Deep Networks. *22*(1), 4687–4740. https://doi.org/10.5555/3546258.3546362

Jarvis, M. A., Chipps, J., & Padmanabhanunni, A. (2019). “This phone saved my life”: Older persons’ experiences and appraisals of an mHealth intervention aimed at addressing loneliness. *Journal of Psychology in Africa*, *29*(2), 159–166. https://doi.org/10.1080/14330237.2019.1594650

Jenkins, K., McCauley, D., Heffron, R., Stephan, H., & Rehner, R. (2016). Energy justice: A conceptual review. *Energy Research & Social Science*, *11*, 174–182. https://doi.org/10.1016/j.erss.2015.10.004

Jentoft, E. E., Sandset, T., & Haldar, M. (2025). Problematizing loneliness as a public health issue: An analysis of policy in the United Kingdom. *Critical Policy Studies*, *19*(1), 1–18. https://doi.org/10.1080/19460171.2024.2306240

Ji, S., Zhang, T., Yang, K., Ananiadou, S., & Cambria, E. (2023, December 17). *Rethinking Large Language Models in Mental Health Applications*. arXiv: 2311.11267 [cs]. https://doi.org/10.48550/arXiv.2311.11267

Jiang, Y., Jiang, Y., Leqi, L., & Winkielman, P. (2022). Many Ways to Be Lonely Fine Grained Characterization of Loneliness and Its Potential Changes in COVID 19. *Proceedings of the International AAAI Conference on Web and Social Media*, *16*, 405–416. https://doi.org/10.1609/icwsm.v16i1.19302

Johnson, K. T., Zawadzki, M. J., & Kho, C. (2024). Loneliness and sleep in everyday life: Using ecological momentary assessment to characterize the shape of daily loneliness experience. *Sleep Health*, *10*(4), 508–514. https://doi.org/10.1016/j.sleh.2024.04.003

Joloudari, J. H., Marefat, A., Nematollahi, M. A., Oyelere, S. S., & Hussain, S. (2023). Effective Class-Imbalance Learning Based on SMOTE and Convolutional Neural Networks. *Applied Sciences*, *13*(6), 4006. https://doi.org/10.3390/app13064006

Jones, A. (Februray 2022). *Person-Centred Retrofit A fuel poverty vulnerability led approac* (Summary Report). Retrieved April 14, 2023, from https://carbon.coop/2022/01/person-centred-retrofit-a-fuel-poverty-vulnerability-led-approach-report-launch/

Jones, E. (1984). *Social Stigma: The Psychology of Marked Relationships*. W.H.Freeman & Co Ltd.

Jong-Gierveld, J. de, & Tilburg, T. V. (1999). Manual De Jong GIerveld Loneliness Scale. https://doi.org/10.17605/OSF.IO/U6GCK

Jovicic, A., & McPherson, S. (2020). To support and not to cure: General practitioner management of loneliness. *Health & Social Care in the Community*, *28*(2), 376–384. https://doi.org/10.1111/hsc.12869

Kang, J. eun, Graham-Engeland, J. E., Scott, S., Smyth, J. M., & Sliwinski, M. J. (2024). The relationship between loneliness and the experiences of everyday stress and stressor-related emotion. *Stress and Health*, *40*(2), e3294. https://doi.org/10.1002/smi.3294

Kaveladze, B. T., Gastelum, S. F., Ngo, D.-A. C., Delacruz, P., Cohen, K. A., Käll, A., Andersson, G., Schleider, J. L., & Schueller, S. M. (2025). A randomized controlled trial comparing brief online self-guided interventions for loneliness. *Journal of Consulting and Clinical Psychology*, *93*(1), 54–63. https://doi.org/10.1037/ccp0000908

Kearns, A., Whitley, E., Tannahill, C., & Ellaway, A. (2015). Loneliness, social relations and health and well-being in deprived communities. *Psychology, Health & Medicine*, *20*(3), 332–344. https://doi.org/10.1080/13548506.2014.940354

Kerr, N. A., & Stanley, T. B. (2021). Revisiting the social stigma of loneliness. *Personality and Individual Differences*, *171*, 110482. https://doi.org/10.1016/j.paid.2020.110482

Kessler, R. C., Barker, P. R., Colpe, L. J., Epstein, J. F., Gfroerer, J. C., Hiripi, E., Howes, M. J., Normand, S.-L. T., Manderscheid, R. W., Walters, E. E., & Zaslavsky, A. M. (2003). Screening for Serious Mental Illness in the General Population. *Archives of General Psychiatry*, *60*(2), 184. https://doi.org/10.1001/archpsyc.60.2.184

Keum, H., Cevik, E., Kim, J., Demirlenk, Y. M., Atar, D., Saini, G., Sheth, R. A., Deipolyi, A. R., & Oklu, R. (2024). Tissue Ablation: Applications and Perspectives. *Advanced Materials*, *36*(32), 2310856. https://doi.org/10.1002/adma.202310856

Kherwa, P., & Bansal, P. (2018). Topic Modeling: A Comprehensive Review. *ICST Transactions on Scalable Information Systems*, *0*(0), 159623. https://doi.org/10.4108/eai.13-7-2018.159623

Killgore, W. D. S., Cloonan, S. A., Taylor, E. C., Lucas, D. A., & Dailey, N. S. (2020). Loneliness during the first half-year of COVID-19 Lockdowns. *Psychiatry Research*, *294*, 113551. https://doi.org/10.1016/j.psychres.2020.113551

Killgore, W. D. S., Cloonan, S. A., Taylor, E. C., Miller, M. A., & Dailey, N. S. (2020). Three months of loneliness during the COVID-19 lockdown. *Psychiatry Research*, *293*, 113392. https://doi.org/10.1016/j.psychres.2020.113392

Kiritchenko, S., Hipson, W., Coplan, R., & Mohammad, S. M. (2020). SOLO: A Corpus of Tweets for Examining the State of Being Alone. *The 12th Conference on Language Resources and Evaluation*, 1567–1577. https://aclanthology.org/2020.lrec-1.195/

Kirova, A. (2001). Loneliness in Immigrant Children: Implications for Classroom Practice. *Childhood Education*. Retrieved January 9, 2026, from https://www.tandfonline.com/doi/abs/10.1080/00094056.2001.10521648

Kivran-Swaine, F., Ting, J., Brubaker, J., Teodoro, R., & Naaman, M. (2014). Understanding Loneliness in Social Awareness Streams: Expressions and Responses. *Proceedings of the International AAAI Conference on Web and Social Media*, *8*(1), 256–265. https://doi.org/10.1609/icwsm.v8i1.14506

Klin, A., & Lemish, D. (2008). Mental Disorders Stigma in the Media: Review of Studies on Production, Content, and Influences. *Journal of Health Communication*, *13*(5), 434–449. https://doi.org/10.1080/10810730802198813

Ko, S. Y., Wei, M., Rivas, J., & Tucker, J. R. (2022). Reliability and Validity of Scores on a Measure of Stigma of Loneliness. *The Counseling Psychologist*, *50*(1), 96–122. https://doi.org/10.1177/00110000211048000

Koh, J. X., & Liew, T. M. (2022). How loneliness is talked about in social media during COVID-19 pandemic: Text mining of 4,492 Twitter feeds. *Journal of Psychiatric Research*, *145*, 317–324. https://doi.org/10.1016/j.jpsychires.2020.11.015

Kroenke, K., Spitzer, R. L., & Williams, J. B. W. (2001). The PHQ-9: Validity of a brief depression severity measure. *Journal of General Internal Medicine*, *16*(9), 606–613. https://doi.org/10.1046/j.1525-1497.2001.016009606.x

Kumar, V., Sattar, Y., Bseiso, A., Khan, S., & Rutkofsky, I. H. (2021). The Effectiveness of Internet-Based Cognitive Behavioral Therapy in Treatment of Psychiatric Disorders. *Cureus*, *9*(8), e1626. https://doi.org/10.7759/cureus.1626

Kung, C. S. J., Pudney, S. E., & Shields, M. A. (2022). Economic gradients in loneliness, social isolation and social support: Evidence from the UK Biobank. *Social Science & Medicine*, *306*, 115122. https://doi.org/10.1016/j.socscimed.2022.115122

Kwan, B., & Rickwood, D. J. (2015). A systematic review of mental health outcome measures for young people aged 12 to 25 years. *BMC Psychiatry*, *15*(1), 279. https://doi.org/10.1186/s12888-015-0664-x

Lai, V., Cai, J. Z., & Tan, C. (2019, October 18). *Many Faces of Feature Importance: Comparing Built-in and Post-hoc Feature Importance in Text Classification*. arXiv: 1910.08534 [cs]. https://doi.org/10.48550/arXiv.1910.08534

Lau, S., & Gruen, G. E. (1992). The Social Stigma of Loneliness: Effect of Target Person's and Perceiver's Sex. *Personality and Social Psychology Bulletin*, *18*(2), 182–189. https://doi.org/10.1177/0146167292182009

Laustsen, L. M., Christiansen, J., Maindal, H. T., Plana-Ripoll, O., & Lasgaard, M. (2024). The longitudinal relation between loneliness and perceived stress: A structural equation modelling analysis of 10,159 individuals. *Scandinavian Journal of Public Health*, *52*(4), 410–418. https://doi.org/10.1177/14034948231151716

Lawn, S., Kaine, C., Stafrace, S., Backman-Hoyle, D., Lavranos, E., Jefferies, B., Byrne, S., Kaur, M., Giordani, G., Matthews, L., & Mathews, S. (2023). Why talking about loneliness matters to the mental health of consumers and to the work of the psychiatrist. *Australian & New Zealand Journal of Psychiatry*, *57*(4), 469–471. https://doi.org/10.1177/00048674231159622

Lawrence, H. R., Schneider, R. A., Rubin, S. B., Matarić, M. J., McDuff, D. J., & Bell, M. J. (2024). The Opportunities and Risks of Large Language

Models in Mental Health. *JMIR Mental Health*, *11*(1), e59479. https://doi.org/10.2196/59479

Lee, J., Yoon, W., Kim, S., Kim, D., Kim, S., So, C. H., & Kang, J. (2020). BioBERT: A pre-trained biomedical language representation model for biomedical text mining (J. Wren, Ed.). *Bioinformatics*, *36*(4), 1234–1240. https://doi.org/10.1093/bioinformatics/btz682

Lehtimaki, S., Martic, J., Wahl, B., Foster, K. T., & Schwalbe, N. (2021). Evidence on Digital Mental Health Interventions for Adolescents and Young People: Systematic Overview. *JMIR Mental Health*, *8*(4), e25847. https://doi.org/10.2196/25847

Leung, C. W., Laraia, B. A., Feiner, C., Solis, K., Stewart, A. L., Adler, N. E., & Epel, E. S. (2022). The Psychological Distress of Food Insecurity: A Qualitative Study of the Emotional Experiences of Parents and Their Coping Strategies. *Journal of the Academy of Nutrition and Dietetics*, *122*(10), 1903–1910.e2. https://doi.org/10.1016/j.jand.2022.05.010

Li, T. M. H., Chen, J., Law, F. O. C., Li, C.-T., Chan, N. Y., Chan, J. W. Y., Chau, S. W. H., Liu, Y., Li, S. X., Zhang, J., Leung, K.-S., & Wing, Y.-K. (2023). Detection of Suicidal Ideation in Clinical Interviews for Depression Using Natural Language Processing and Machine Learning: Cross-Sectional Study. *JMIR Medical Informatics*, *11*(1), e50221. https://doi.org/10.2196/50221

Lim, M. H., Eres, R., & Vasan, S. (2020). Understanding loneliness in the twenty-first century: An update on correlates, risk factors, and potential solutions. *Social Psychiatry and Psychiatric Epidemiology*, *55*(7), 793–810. https://doi.org/10.1007/s00127-020-01889-7

Lim, M. H., Rodebaugh, T. L., Eres, R., Long, K. M., Penn, D. L., & Gleeson, J. F. M. (2019). A Pilot Digital Intervention Targeting Loneliness in Youth Mental Health. *Frontiers in Psychiatry*, *10*. https://doi.org/10.3389/fpsyt.2019.00604

Link, B. G., & Phelan, J. C. (2001). Conceptualizing Stigma. *Annual Review of Sociology*, *27*, 363–385. https://doi.org/10.1146/annurev.soc.27.1.363

Link, B. G., Yang, L. H., Phelan, J. C., & Collins, P. Y. (2004). Measuring mental illness stigma. *Schizophrenia Bulletin*, *30*(3), 511–541. https://doi.org/10.1093/oxfordjournals.schbul.a007098

Lipton, Z. C., & Steinhardt, J. (2019). Troubling Trends in Machine Learning Scholarship: Some ML papers suffer from flaws that could mislead the public and stymie future research. *Queue*, *17*(1), 45–77. https://doi.org/10.1145/3317287.3328534

Liu, Z., Peach, R. L., Lawrance, E. L., Noble, A., Ungless, M. A., & Barahona, M. (2021). Listening to Mental Health Crisis Needs at Scale: Using Natural Language Processing to Understand and Evaluate a Mental Health Crisis Text Messaging Service. *Frontiers in Digital Health*, *3*, 779091. https://doi.org/10.3389/fdgth.2021.779091

Luchetti, M., Lee, J. H., Aschwanden, D., Sesker, A., Strickhouser, J. E., Terracciano, A., & Sutin, A. R. (2020). The trajectory of loneliness in response to COVID-19. *American Psychologist*, *75*(7), 897–908. https://doi.org/10.1037/amp0000690

Ludwig, K. A., Brandrett, B., Lim, M. H., Mihas, P., & Penn, D. L. (2022). Lived experience of loneliness in psychosis: A qualitative approach.

Journal of Mental Health, *31*(4), 543–550. https://doi.org/10.1080/09638237.2021.2022622

Lykes, V. A., & Kemmelmeier, M. (2014). What Predicts Loneliness? Cultural Difference Between Individualistic and Collectivistic Societies in Europe. *Journal of Cross-Cultural Psychology*, *45*(3), 468–490. https://doi.org/10.1177/0022022113509881

Lyons, M., Gupta, V., Blaney, P. S., Ogenyi, A., Webster, E., & Brewer, G. (2024). RETRACTED ARTICLE: The complex lived experience of schizophrenia diagnosis: A thematic analysis of online forum posts. *Current Psychology*, *43*(30), 24878–24889. https://doi.org/10.1007/s12144-024-06175-2

Lyyra, N., Thorsteinsson, E. B., Eriksson, C., Madsen, K. R., Tolvanen, A., Löfstedt, P., & Välimaa, R. (2021). The Association between Loneliness, Mental Well-Being, and Self-Esteem among Adolescents in Four Nordic Countries. *International Journal of Environmental Research and Public Health*, *18*(14), 7405. https://doi.org/10.3390/ijerph18147405

Macdonald, S., Nixon, J., & Deacon, L. (2018). 'Loneliness in the city': Examining socio-economics, loneliness and poor health in the North East of England. *Public Health*, *165*, 88–94. https://doi.org/10.1016/j.puhe.2018.09.003

Madsen, K., Tjørnhøj-Thomsen, T., Jervelund, S. S., Qualter, P., & Holstein, B. E. (2021). Lonely, but Not Alone: Qualitative Study among Immigrant and Native-Born Adolescents. *International Journal of Environmental Research and Public Health*, *18*(21), 11425. https://doi.org/10.3390/ijerph182111425

Maes, M., Qualter, P., Lodder, G. M. A., & Mund, M. (2022). How (Not) to Measure Loneliness: A Review of the Eight Most Commonly Used Scales. *International Journal of Environmental Research and Public Health*, *19*(17), 10816. https://doi.org/10.3390/ijerph191710816

Maes, M., Qualter, P., Vanhalst, J., Van den Noortgate, W., & Goossens, L. (2019). Gender Differences in Loneliness across the Lifespan: A Meta–Analysis. *European Journal of Personality*, *33*(6), 642–654. https://doi.org/10.1002/per.2220

Malcom, D. R. (2021). Loneliness as a Downstream Concern in a Pandemic (and Post-Pandemic) World. *American Journal of Pharmaceutical Education*, *85*(4). https://doi.org/10.5688/ajpe8456

Mann, F., Wang, J., Pearce, E., Ma, R., Schlief, M., Lloyd-Evans, B., Ikhtabi, S., & Johnson, S. (2022). Loneliness and the onset of new mental health problems in the general population. *Social Psychiatry and Psychiatric Epidemiology*, *57*(11), 2161–2178. https://doi.org/10.1007/s00127-022-02261-7

Mansfield, K. E., Mathur, R., Tazare, J., Henderson, A. D., Mulick, A. R., Carreira, H., Matthews, A. A., Bidulka, P., Gayle, A., Forbes, H., Cook, S., Wong, A. Y. S., Strongman, H., Wing, K., Warren-Gash, C., Cadogan, S. L., Smeeth, L., Hayes, J. F., Quint, J. K., ... Langan, S. M. (2021). Indirect acute effects of the COVID-19 pandemic on physical and mental health in the UK: A population-based study. *The Lancet Digital Health*, *3*(4), e217–e230. https://doi.org/10.1016/S2589-7500(21)00017-0

Manzo, J. (2004). On the Sociology and Social Organization of Stigma: Some Ethnomethodological Insights. *Human Studies*, *27*(4), 401–416. https://doi.org/10.1007/s10746-004-3338-0

Martin, K. E., Wood, L. J., Houghton, S., Carroll, A., & Hattie, J. (2014). 'I Don't have the Best Life': A Qualitative Exploration of Adolescent Loneliness. *Journal of Child and Adolescent Behavior*, *2*(5), 1–7. https://doi.org/10.4172/2375-4494.1000169

Martin, M., Maddocks, E., Chen, Y., Gilman, S., & Colman, I. (2016). Food insecurity and mental illness: Disproportionate impacts in the context of perceived stress and social isolation. *Public Health*, *132*, 86–91. https://doi.org/10.1016/j.puhe.2015.11.014

McNeeley, S. (2012). Sensitive Issues in Surveys: Reducing Refusals While Increasing Reliability and Quality of Responses to Sensitive Survey Items. In L. Gideon (Ed.), *Handbook of Survey Methodology for the Social Sciences* (pp. 377–396). Springer New York. https://doi.org/10.1007/978-1-4614-3876-2_22

Meyes, R., Lu, M., Puiseau, C. W. de, & Meisen, T. (2019, February 18). *Ablation Studies in Artificial Neural Networks*. arXiv: 1901.08644 [cs]. https://doi.org/10.48550/arXiv.1901.08644

Michaelson, J., Jeffrey, K., & Abdallah, S. (2017, February 20). *The Cost of Loneliness to UK Employers*. New Economics Foundation and Co-Op Foundation. Retrieved October 7, 2024, from https://assets.ctfassets.net/5ywmq66472jr/24Nr2598xKAwSiAciwYAmK/3b10bc1c3999df76882d0b0f4e85d53 NEF_COST-OF-LONELINESS_DIGITAL.pdf

Milligan, G., Bernard, A., Dowthwaite, L., Vallejos, E. P., Davis, J., Salhi, L., & Goulding, J. (2024a). Developing a single-session outcome measure using natural language processing on digital mental health transcripts. *Counselling and Psychotherapy Research*, *24*(3), 1057–1068. https://doi.org/10.1002/capr.12766

Milligan, G., Bernard, A., Dowthwaite, L., Vallejos, E. P., Davis, J., Salhi, L., & Goulding, J. (2024b). Developing a single-session outcome measure using natural language processing on digital mental health transcripts. *Counselling and Psychotherapy Research*, *24*(3), 1057–1068. https://doi.org/10.1002/capr.12766

Mindel, C., Oppong, C., Rothwell, E., Sefi, A., & Jacob, J. (2021). Assessing the need of young people using online counselling services: How useful are standardised measures? *Child and Adolescent Mental Health*, *26*(4), 339–346. https://doi.org/10.1111/camh.12456

Morrish, N., & Medina-Lara, A. (2021). Does unemployment lead to greater levels of loneliness? A systematic review. *Social Science & Medicine*, *287*, 114339. https://doi.org/10.1016/j.socscimed.2021.114339

Mund, M., Maes, M., Drewke, P. M., Gutzeit, A., Jaki, I., & Qualter, P. (2022). Would the Real Loneliness Please Stand Up? The Validity of Loneliness Scores and the Reliability of Single-Item Scores. *Assessment*, 107319112210772. https://doi.org/10.1177/10731911221077227

Mushtaq, R. (2014). Relationship Between Loneliness, Psychiatric Disorders and Physical Health ? A Review on the Psychological Aspects of Loneliness. *JOURNAL OF CLINICAL AND DIAGNOSTIC RESEARCH*. https://doi.org/10.7860/JCDR/2014/10077.4828

Narla, A., Kuprel, B., Sarin, K., Novoa, R., & Ko, J. (2018). Automated Classification of Skin Lesions: From Pixels to Practice. *Journal of Investigative Dermatology*, *138*(10), 2108–2110. https://doi.org/10.1016/j.jid.2018.06.175

Neves, B. B., & Petersen, A. (2025). The social stigma of loneliness: A sociological approach to understanding the experiences of older people. *The Sociological Review*, *73*(2), 362–383. https://doi.org/10.1177/00380261231212100

Ng, Q. X., Lee, D. Y. X., Yau, C. E., Lim, Y. L., Ng, C. X., & Liew, T. M. (2023). Examining the Public Messaging on 'Loneliness' over Social Media: An Unsupervised Machine Learning Analysis of Twitter Posts over the Past Decade. *Healthcare*, *11*(10), 1485. https://doi.org/10.3390/healthcare11101485

Nguyen, T.-v. T., Ryan, R. M., & Deci, E. L. (2018). Solitude as an Approach to Affective Self-Regulation. *Personality and Social Psychology Bulletin*, *44*(1), 92–106. https://doi.org/10.1177/0146167217733073

NHS England. (2023, May 16). *The Health Survey for England 2021* (Report and Dataset). https://digital.nhs.uk/data-and-information/publications/statistical/health-survey-for-england/2021-part-2

Nica-Avram, G., Harvey, J., Smith, G., Smith, A., & Goulding, J. (2021). Identifying food insecurity in food sharing networks via machine learning. *Journal of Business Research*, *131*, 469–484. https://doi.org/10.1016/j.jbusres.2020.09.028

Nowland, R., Thomson, G., McNally, L., Smith, T., & Whittaker, K. (2021). Experiencing loneliness in parenthood: A scoping review. *Perspectives in Public Health*, *141*(4), 214–225. https://doi.org/10.1177/17579139211018243

Nwabueze, K. K., Akubue, N., Onakoya, A., Okolieze, S. C., Otaniyen-Igbinoba, I. J., Chukwunonye, C., Okengwu, C. G., Ige, T., Alao, O. J., & Adindu, K. N. (2025). Exploring the prevalence and risk factors of adolescent mental health issues in the COVID and post-COVID era in the U.K.: A systematic review. *EXCLI Journal*, *24*, 508–523. https://doi.org/10.17179/excli2025-8325

Nyqvist, F., Nygård, M., & Scharf, T. (2019). Loneliness amongst older people in Europe: A comparative study of welfare regimes. *European Journal of Ageing*, *16*(2), 133–143. https://doi.org/10.1007/s10433-018-0487-y

Office for National Statistics. (2018a). *Testing of loneliness questions in surveys*. https://www.ons.gov.uk/peoplepopulationandcommunity/wellbeing/compendium/nationalmeasurementofloneliness/2018/testingoflonelinessque questions-and-response-options-tested

Office for National Statistics. (2018b, December 5). *Cognitive testing of loneliness questions and response options - Office for National Statistics*. Office for National Stastics. Retrieved September 29, 2025, from https://www.ons.gov.uk/peoplepopulationandcommunity/wellbeing/compendium/nationalmeasurementofloneliness/2018/cognitivetestingoflonelinessquestionsandrespon

Office for National Statistics. (2023, February 13). *Characteristics of adults experiencing energy and food insecurity in Great Britain: 22 November to 18 December 2022*. Retrieved April 13, 2023, from https://www.ons.gov.uk/peoplepopulationandcommunity/wellbeing/articles/characteristicsofadultsexperiencingenergyandfoodinsecuritygreatbritain/

22novemberto18december2022#characteristics-associated-with-experiencing-energy-insecurity

Office for National Statistics. (2024, October 18). *Public opinions and social trends, Great Britain 2024* (Statistical Bulletin). Retrieved October 22, 2024, from https://www.ons.gov.uk/peoplepopulationandcommunity/wellbeing/bulletins/publicopinionsandsocialtrendsgreatbritain/latest

Office for National Statistics. (2025, August 15). *Public opinions and social trends, Great Britain: July 2025* (Statistical Bulletin). The Office for National Statistics. Retrieved September 5, 2025, from https://www.ons.gov.uk/peoplepopulationandcommunity/wellbeing/bulletins/publicopinionsandso
july2025

O'Rourke, H. M., Collins, L., & Sidani, S. (2018). Interventions to address social connectedness and loneliness for older adults: A scoping review. *BMC Geriatrics*, *18*(1), 214. https://doi.org/10.1186/s12877-018-0897-x

Oseguera, O., Rinaldi, A., Tuazon, J., & Cruz, A. C. (2017). Automatic Quantification of the Veracity of Suicidal Ideation in Counseling Transcripts. In C. Stephanidis (Ed.), *HCI International 2017 – Posters' Extended Abstracts* (pp. 473–479). Springer International Publishing. https://doi.org/10.1007/978-3-319-58750-9_66

Pandey, H. M. (2024, December 13). *Harnessing Large Language Models for Mental Health: Opportunities, Challenges, and Ethical Considerations*. arXiv: 2501.10370 [cs]. https://doi.org/10.48550/arXiv.2501.10370

Park, C., Majeed, A., Gill, H., Tamura, J., Ho, R. C., Mansur, R. B., Nasri, F., Lee, Y., Rosenblat, J. D., Wong, E., & McIntyre, R. S. (2020). The Effect of Loneliness on Distinct Health Outcomes: A Comprehensive Review and Meta-Analysis. *Psychiatry Research*, *294*, 113514. https://doi.org/10.1016/j.psychres.2020.113514

Park, S., & Berkowitz, S. A. (2024). Social Isolation, Loneliness, and Quality of Life Among Food-Insecure Adults. *American Journal of Preventive Medicine*, *67*(1), 120–123. https://doi.org/10.1016/j.amepre.2024.02.001

Paton, E., Jones, E. P., Peprah, J., & Benson, M. (2024). Our words matter: Finding consensus on evolving and personal language around suicide, mental health concerns and alcohol and other drug use. *Media International Australia*, *193*(1), 80–95. https://doi.org/10.1177/1329878X241278005

Penning, M. J., Liu, G., & Chou, P. H. B. (2014). Measuring Loneliness Among Middle-Aged and Older Adults: The UCLA and de Jong Gierveld Loneliness Scales. *Social Indicators Research*, *118*(3), 1147–1166. https://doi.org/10.1007/s11205-013-0461-1

Perissinotto, C. M., Stijacic Cenzer, I., & Covinsky, K. E. (2012). Loneliness in Older Persons: A Predictor of Functional Decline and Death. *Archives of Internal Medicine*, *172*(14), 1078–1084. https://doi.org/10.1001/archinternmed.2012.1993

Perlman, D., & Peplau, L. A. (1981). Toward a social psychology of loneliness. *Personal relationships*, *3*, 31–56.

Pettigrew, S., & Roberts, M. (2008). Addressing loneliness in later life. *Aging & Mental Health*, *12*(3), 302–309. https://doi.org/10.1080/13607860802121084

Pierce, M., Hope, H., Ford, T., Hatch, S., Hotopf, M., John, A., Kontopantelis, E., Webb, R., Wessely, S., McManus, S., & Abel, K. M. (2020). Mental health before and during the COVID-19 pandemic: A longitudinal probability sample survey of the UK population. *The Lancet Psychiatry*, *7*(10), 883–892. https://doi.org/10.1016/S2215-0366(20)30308-4

Pineau, C., Williams, P. L., Brady, J., Waddington, M., & Frank, L. (2021). Exploring experiences of food insecurity, stigma, social exclusion, and shame among women in high-income countries: A narrative review. *Canadian Food Studies / La Revue canadienne des études sur l'alimentation*, *8*(3). https://doi.org/10.15353/cfs-rcea.v8i3.473

Ponizovsky, A. M., & Ritsner, M. S. (2004). Patterns of loneliness in an immigrant population. *Comprehensive Psychiatry*, *45*(5), 408–414. https://doi.org/10.1016/j.comppsych.2004.03.011

Pourmotabbed, A., Moradi, S., Babaei, A., Ghavami, A., Mohammadi, H., Jalili, C., Symonds, M. E., & Miraghajani, M. (2020). Food insecurity and mental health: A systematic review and meta-analysis. *Public Health Nutrition*, *23*(10), 1778–1790. https://doi.org/10.1017/S136898001900435X

Powell, M., & Miller, R. (2016). Seventy Years of Privatizing the British National Health Service? *Social Policy & Administration*, *50*(1), 99–118. https://doi.org/10.1111/spol.12161

Prizeman, K., Weinstein, N., & McCabe, C. (2023). Effects of mental health stigma on loneliness, social isolation, and relationships in young people with depression symptoms. *BMC Psychiatry*, *23*(1), 527. https://doi.org/10.1186/s12888-023-04991-7

Qualter, P., Vanhalst, J., Harris, R., Van Roekel, E., Lodder, G., Bangee, M., Maes, M., & Verhagen, M. (2015). Loneliness Across the Life Span. *Perspectives on Psychological Science*, *10*(2), 250–264. https://doi.org/10.1177/1745691615568999

Rasmy, L., Xiang, Y., Xie, Z., Tao, C., & Zhi, D. (2021). Med-BERT: Pretrained contextualized embeddings on large-scale structured electronic health records for disease prediction. *npj Digital Medicine*, *4*(1), 86. https://doi.org/10.1038/s41746-021-00455-y

Reedman-Flint, D., Harvey, J., Goulding, J., & Priestnall, G. (2022). I Wandered Lonely in the Cloud: A Review of Loneliness, Social Isolation and Digital Footprint Data: *Proceedings of the 6th International Conference on Computer-Human Interaction Research and Applications*, 225–235. https://doi.org/10.5220/0011578500003323

Reinhard, M. A., & Padberg, F. (2025). Developing loneliness interventions for people with personality disorders: A call to action. *Annals of the New York Academy of Sciences*, *1548*(1), 56–65. https://doi.org/10.1111/nyas.15367

Reupert, A., Gladstone, B., Helena Hine, R., Yates, S., McGaw, V., Charles, G., Drost, L., & Foster, K. (2021). Stigma in relation to families living with parental mental illness: An integrative review. *International Jour-*

nal of Mental Health Nursing, *30*(1), 6–26. https://doi.org/10.1111/inm.12820

Reutter, L. I., Stewart, M. J., Veenstra, G., Love, R., Raphael, D., & Makwarimba, E. (2009). “Who Do They Think We Are, Anyway?”: Perceptions of and Responses to Poverty Stigma. *Qualitative Health Research*, *19*(3), 297–311. https://doi.org/10.1177/1049732308330246

Rickman, S., Fernandez, J.-L., & Malley, J. (2025). Understanding patterns of loneliness in older long-term care users using natural language processing with free text case notes. *PLOS ONE*, *20*(4), e0319745. https://doi.org/10.1371/journal.pone.0319745

Rokach, A., & Patel, K. (2024). The health consequences of loneliness. *Environment and Social Psychology*, *9*(6). https://doi.org/10.54517/esp.v9i6.2150

Rook, K. S. (1984). Promoting social bonding: Strategies for helping the lonely and socially isolated. *American Psychologist*, *39*(12), 1389–1407. https://doi.org/10.1037/0003-066X.39.12.1389

Rose, D., Evans, J., Sweeney, A., & Wykes, T. (2011). A model for developing outcome measures from the perspectives of mental health service users. *International Review of Psychiatry*, *23*(1), 41–46. https://doi.org/10.3109/09540261.2010.545990

Rostila, M. (2007). Social capital and health in European welfare regimes: A multilevel approach. *Journal of European Social Policy*, *17*(3), 223–239. https://doi.org/10.1177/0958928707078366

Rotenberg, K. J., Bartley, J. L., & Toivonen, D. M. (1997). Children’s Stigmatization of Chronic Loneliness in Peers. *Journal of Social Behavior and Personality*, *12*(2), 577–584. Retrieved September 19, 2025, from https://www.proquest.com/docview/1292310546/citation/F4A28722F83E4B43PQ/1

Rothstein, B., & Stolle, D. (2003). Social Capital, Impartiality and the Welfare State: An Institutional Approach. In M. Hooghe & D. Stolle (Eds.), *Generating Social Capital* (pp. 191–209). Palgrave Macmillan US. https://doi.org/10.1057/9781403979544_10

Ruan, J., Xu, Y.-M., & Zhong, B.-L. (2023). Loneliness in older Chinese adults amid the COVID-19 pandemic: Prevalence and associated factors. *Asia-Pacific Psychiatry*, *15*(4), e12543. https://doi.org/10.1111/appy.12543

Rumas, R., Shamblaw, A. L., Jagtap, S., & Best, M. W. (2021). Predictors and consequences of loneliness during the COVID-19 Pandemic. *Psychiatry Research*, *300*, 113934. https://doi.org/10.1016/j.psychres.2021.113934

Russell, D. (1982, January). The measurement of loneliness. In *The measurement of loneliness* (pp. 81–104).

Russell, D., Peplau, L. A., & Cutrona, C. E. (1980). The revised UCLA Loneliness Scale: Concurrent and discriminant validity evidence. *Journal of Personality and Social Psychology*, *39*(3), 472–480. https://doi.org/10.1037//0022-3514.39.3.472

Russell, D., Peplau, L. A., & Ferguson, M. L. (1978). Developing a measure of loneliness. *Journal of Personality Assessment*, *42*(3), 290–294. https://doi.org/10.1207/s15327752jpa4203_11

Russell, D. W. (1996). UCLA Loneliness Scale (Version 3): Reliability, Validity, and Factor Structure. *Journal of Personality Assessment*, *66*(1), 20–40. https://doi.org/10.1207/s15327752jpa6601_2

Ryu, J., Heisig, S., McLaughlin, C., Bortz, R., Katz, M., & Gu, X. (2021). A natural language processing approach to modelling treatment alliance in psychotherapy transcripts. *BJPsych Open*, *7*(S1), S48–S48. https://doi.org/10.1192/bjo.2021.177

Salari, N., Razavizadeh, S., Abdolmaleki, A., Zarei, H., Daneshkhah, A., & Mohammadi, M. (2025). Global prevalence of loneliness in immigrants: A systematic review and meta-analysis. *Asian Journal of Psychiatry*, *104*, 104381. https://doi.org/10.1016/j.ajp.2025.104381

Sansone-Pollock, M., Mutrie, N., Guerra, C., Sechi, C., Mula, S., & Calia, C. (2025). COVID-19: Physical Activity, Government Restrictions, and Mental Health in the UK and Italy. *Trends in Psychology*, *33*(2), 383–400. https://doi.org/10.1007/s43076-023-00262-2

Saunders, B., Sim, J., Kingstone, T., Baker, S., Waterfield, J., Bartlam, B., Burroughs, H., & Jinks, C. (2018). Saturation in qualitative research: Exploring its conceptualization and operationalization. *Quality & Quantity*, *52*(4), 1893–1907. https://doi.org/10.1007/s11135-017-0574-8

Schmidt, N., & Sermat, V. (1983). Measuring loneliness in different relationships. *Journal of Personality and Social Psychology*, *44*(5), 1038–1047. https://doi.org/10.1037/0022-3514.44.5.1038

Schobin, J. (2022). Loneliness and Emancipation: A Multilevel Analysis of the Connection between Gender Inequality, Loneliness, and Social Isolation in the ISSP 2017. *International Journal of Environmental Research and Public Health*, *19*(12), 7428. https://doi.org/10.3390/ijerph19127428

Schueller, S. M., & Torous, J. (2020). Scaling evidence-based treatments through digital mental health. *The American Psychologist*, *75*(8), 1093–1104. https://doi.org/10.1037/amp0000654

Schwartz, H. A., Sap, M., Kern, M. L., Eichstaedt, J. C., Kapelner, A., Agrawal, M., Blanco, E., Dziurzynski, L., Park, G., Stillwell, D., Kosinski, M., Seligman, M. E., & Ungar, L. H. (2016). Predicting Individual Well-Being Through the Language of Social Media. *Biocomputing 2016*, 516–527. https://doi.org/10.1142/9789814749411_0047

Scotish Government. (2023, March 8). *Social isolation and loneliness: Recovering our Connections 2023 to 2026* (Strategy/plan). Scotish Government. Retrieved September 18, 2025, from https://www.gov.scot/publications/recovering-connections-2023-2026/pages/6/

Segel-Karpas, D., Ayalon, L., & Lachman, M. E. (2018). Loneliness and depressive symptoms: The moderating role of the transition into retirement. *Aging & Mental Health*, *22*(1), 135–140. https://doi.org/10.1080/13607863.2016.1226770

Semple, T., Rodrigues, L., Harvey, J., Figueredo, G., Nica-Avram, G., Gillott, M., Milligan, G., & Goulding, J. (2024). An empirical critique of the low income low energy efficiency approach to measuring fuel poverty. *Energy Policy*, *186*, 114014. https://doi.org/10.1016/j.enpol.2024.114014

Shah, D. S., Schwartz, H. A., & Hovy, D. (2020). Predictive Biases in Natural Language Processing Models: A Conceptual Framework and Overview. *Proceedings of the 58th Annual Meeting of the Association for Compu-*

tational Linguistics, 5248–5264. https://doi.org/10.18653/v1/2020.acl-main.468

Shahid, A., Chung, J., & Heo, S. (2025). Exploring Older Adults Personality Preferences for LLM-powered Conversational Companions. *Proceedings of the Extended Abstracts of the CHI Conference on Human Factors in Computing Systems*, 1–7. https://doi.org/10.1145/3706599.3719976

Shankar, A. (2017, June 28). Loneliness and Health. In *Oxford Research Encyclopedia of Psychology*. https://doi.org/10.1093/acrefore/9780190236557.013.122

Sheikholeslami, S., Ghasemirahni, H., Payberah, A. H., Wang, T., Dowling, J., & Vlassov, V. (2025). Utilizing Large Language Models for Ablation Studies in Machine Learning and Deep Learning. *Proceedings of the 5th Workshop on Machine Learning and Systems*, 230–237. https://doi.org/10.1145/3721146.3721957

Sheikholeslami, S., Meister, M., Wang, T., Payberah, A. H., Vlassov, V., & Dowling, J. (2021). AutoAblation: Automated Parallel Ablation Studies for Deep Learning. *Proceedings of the 1st Workshop on Machine Learning and Systems*, 55–61. https://doi.org/10.1145/3437984.3458834

Shields, M. A., & Price, S. W. (2005). Exploring the Economic and Social Determinants of Psychological Well-Being and Perceived Social Support in England. *Journal of the Royal Statistical Society Series A: Statistics in Society*, *168*(3), 513–537. https://doi.org/10.1111/j.1467-985X.2005.00361.x

Shiovitz-Ezra, S., & Ayalon, L. (2012). Use of Direct Versus Indirect Approaches to Measure Loneliness in Later Life. *Research on Aging*, *34*(5), 572–591. https://doi.org/10.1177/0164027511423258

Site, A., Lohan, E. S., Jolanki, O., Valkama, O., Hernandez, R. R., Latikka, R., Alekseeva, D., Vasudevan, S., Afolaranmi, S., Ometov, A., Oksanen, A., Martinez Lastra, J., Nurmi, J., & Fernandez, F. N. (2022). Managing Perceived Loneliness and Social-Isolation Levels for Older Adults: A Survey with Focus on Wearables-Based Solutions. *Sensors*, *22*(3), 1108. https://doi.org/10.3390/s22031108

Site, A., Vasudevan, S., Afolaranmi, S. O., Lastra, J. L. M., Nurmi, J., & Lohan, E. S. (2022). A Machine-Learning-Based Analysis of the Relationships between Loneliness Metrics and Mobility Patterns for Elderly. *Sensors*, *22*(13), 4946. https://doi.org/10.3390/s22134946

Smith, G., Mansilla, R., & Goulding, J. (2020). Model Class Reliance for Random Forests. *34th Conference on Neural Information Processing Systems*.

Society, B. G., & of Psychiatrists London, R. C. (2019). *Position Statement on Loneliness and Social Isolation* (Position Statement). British Geriatric Society/Royal College of Psychiatrists London.

Solano, C. H., Batten, P. G., & Parish, E. A. (1982). Loneliness and patterns of self-disclosure. *Journal of Personality and Social Psychology*, *43*(3), 524–531. https://doi.org/10.1037/0022-3514.43.3.524

Spitzer, R. L., Kroenke, K., Williams, J. B. W., & Löwe, B. (2006). A Brief Measure for Assessing Generalized Anxiety Disorder: The GAD-7. *Archives of Internal Medicine*, *166*(10), 1092. https://doi.org/10.1001/archinte.166.10.1092

Sridhar, S., Kazi, N., Kahanda, I., & McCrory, B. (2021). Psychiatry Transcript Annotation: Process Study and Improvements. *Proceedings of the International Symposium on Human Factors and Ergonomics in Health Care*, *10*(1), 71–75. https://doi.org/10.1177/2327857921101030

Stack, R. J., & Meredith, A. (2018). The Impact of Financial Hardship on Single Parents: An Exploration of the Journey From Social Distress to Seeking Help. *Journal of Family and Economic Issues*, *39*(2), 233–242. https://doi.org/10.1007/s10834-017-9551-6

Stefanidou, T., Wang, J., Morant, N., Lloyd-Evans, B., & Johnson, S. (2021). Loneliness in early psychosis: A qualitative study exploring the views of mental health practitioners in early intervention services. *BMC Psychiatry*, *21*(1), 134. https://doi.org/10.1186/s12888-021-03138-w

Stepanikova, I., Nie, N. H., & He, X. (2010). Time on the Internet at home, loneliness, and life satisfaction: Evidence from panel time-diary data. *Computers in Human Behavior*, *26*(3), 329–338. https://doi.org/10.1016/j.chb.2009.11.002

Stewart, M., Craig, D., MacPherson, K., & Alexander, S. (2001). Promoting positive affect and diminishing loneliness of widowed seniors through a support intervention. *Public Health Nursing (Boston, Mass.)*, *18*(1), 54–63. https://doi.org/10.1046/j.1525-1446.2001.00054.x

Strous, R. D., Koppel, M., Fine, J., Nachliel, S., Shaked, G., & Zivotofsky, A. Z. (2009). Automated Characterization and Identification of Schizophrenia in Writing. *The Journal of Nervous and Mental Disease*, *197*(8), 585–588. https://doi.org/10.1097/NMD.0b013e3181b09068

Sun, J., Ma, S., Fan, Y., & Washington, P. (2024, July 18). *Evaluating Large Language Models for Anxiety and Depression Classification using Counseling and Psychotherapy Transcripts*. arXiv: 2407.13228 [cs]. https://doi.org/10.48550/arXiv.2407.13228

Swales, S., May, C., Nuxoll, M., & Tucker, C. (2020). Neoliberalism, guilt, shame and stigma: A Lacanian discourse analysis of food insecurity. *Journal of Community & Applied Social Psychology*, *30*(6), 673–687. https://doi.org/10.1002/casp.2475

Tani, M., Cheng, Z., Piracha, M., & Wang, B. Z. (2022). Ageing, Health, Loneliness and Wellbeing. *Social Indicators Research*, *160*(2–3), 791–807. https://doi.org/10.1007/s11205-020-02450-4

Teferra, B. G., & Rose, J. (2023). Predicting Generalized Anxiety Disorder From Impromptu Speech Transcripts Using Context-Aware Transformer-Based Neural Networks: Model Evaluation Study. *JMIR Mental Health*, *10*(1), e44325. https://doi.org/10.2196/44325

Terracciano, A., Luchetti, M., Karakose, S., Milad, E., Zavala, D. V., Kekäläinen, T., Stephan, Y., Hajek, A., & Sutin, A. R. (2025). Personality traits and loneliness: An ecological momentary assessment study with self and partner ratings. *Journal of Research in Personality*, *116*, 104607. https://doi.org/10.1016/j.jrp.2025.104607

The Campaign to End Loneliness. (2023). *The State of Loneliness 2023*. Sheffield Hallam University. Retrieved July 31, 2024, from https://www.campaigntoendlonelines org/wp-content/uploads/The-State-of-Loneliness-2023-ONS-data-on-loneliness-in-Britain.pdf

Thunnissen, E., Buffel, V., Reyniers, T., Nöstlinger, C., & Wouters, E. (2022). From Physical Distancing to Social Loneliness among Gay Men and Other Men Having Sex with Men in Belgium: Examining the Disruption of the Social Network and Social Support Structures. *International Journal of Environmental Research and Public Health*, *19*(11), 6873. https://doi.org/10.3390/ijerph19116873

Townsend, P. (1957). *The Family Life of Old People: An Inquiry in East London*. Routledge. https://doi.org/10.4324/9781003433491

Tsamakis, K., Tsiptsios, D., Ouranidis, A., Mueller, C., Schizas, D., Terniotis, C., Nikolakakis, N., Tyros, G., Kympouropoulos, S., Lazaris, A., Spandidos, D. A., Smyrnis, N., & Rizos, E. (2021). COVID-19 and its consequences on mental health (Review). *Experimental and Therapeutic Medicine*, *21*(3), 1–1. https://doi.org/10.3892/etm.2021.9675

Twigg, E., Barkham, M., Bewick, B. M., Mulhern, B., Connell, J., & Cooper, M. (2009). The Young Person's CORE: Development of a brief outcome measure for young people. *Counselling and Psychotherapy Research*, *9*(3), 160–168. https://doi.org/10.1080/14733140902979722

, U. K. (2020, January). *Loneliness Annual Report: The first year* (Policy Paper). Department for Digital, Culture, Media and Sport. https://www.gov.uk/government/publications/loneliness-annual-report-the-first-year

, U. K. (2021). *Loneliness Annual Report January 2021* (Policy Paper). Department for Digital, Culture, Media and Sport. https://www.gov.uk/government/publications/loneliness-annual-report-the-second-year

, U. K. (2022, February). *Tackling Loneliness annual report February 2022: The third year - GOV.UK*. Department for Digital, Culture, Media and Sport. https://www.gov.uk/government/publications/loneliness-annual-report-the-third-year

Vacca, M., Zagaria, A., Fiori, V., Lombardo, C., & Ballesio, A. (2025). Are you Lonesome Tonight? Ecological Momentary Assessment of Evening Loneliness, Worry, and Actigraphic Sleep in Adolescents. *Behavioral Sleep Medicine*, *23*(4), 552–564. https://doi.org/10.1080/15402002.2025.2498364

Vaculíková, J., & Hanková, M. (2023). Loneliness and Mental Health in Response to Early and Late COVID-19 Outbreak: A Cross-Sectional Study of Czech Adults Aged 50 and Over. *Gerontology and Geriatric Medicine*, *9*, 23337214231174129. https://doi.org/10.1177/23337214231174129

Valtorta, N. K., Kanaan, M., Gilbody, S., Ronzi, S., & Hanratty, B. (2016). Loneliness and social isolation as risk factors for coronary heart disease and stroke: Systematic review and meta-analysis of longitudinal observational studies. *Heart*, *102*(13), 1009–1016. https://doi.org/10.1136/heartjnl-2015-308790

van Winkel, M., Wichers, M., Collip, D., Jacobs, N., Derom, C., Thiery, E., Myin-Germeys, I., & Peeters, F. (2017). Unraveling the Role of Loneliness in Depression: The Relationship Between Daily Life Experience and Behavior. *Psychiatry*, *80*(2), 104–117. https://doi.org/10.1080/00332747.2016.1256143

Verity, L., Schellekens, T., Adam, T., Sillis, F., Majorano, M., Wigelsworth, M., Qualter, P., Peters, B., Stajniak, S., & Maes, M. (2021). Tell Me about Loneliness: Interviews with Young People about What Loneliness Is and How to Cope with It. *International Journal of Environmental Research and Public Health*, *18*(22), 11904. https://doi.org/10.3390/ijerph182211904

Verity, L., Yang, K., Nowland, R., Shankar, A., Turnbull, M., & Qualter, P. (2024). Loneliness From the Adolescent Perspective: A Qualitative Analysis of Conversations About Loneliness Between Adolescents and Childline Counselors. *Journal of Adolescent Research*, *39*(5), 1413–1443. https://doi.org/10.1177/07435584221111121

Victor, C. R., & Pikhartova, J. (2020). Lonely places or lonely people? Investigating the relationship between loneliness and place of residence. *BMC Public Health*, *20*(1), 778. https://doi.org/10.1186/s12889-020-08703-8

Victor, C. R., & Yang, K. (2012). The Prevalence of Loneliness Among Adults: A Case Study of the United Kingdom. *The Journal of Psychology*, *146*(1–2), 85–104. https://doi.org/10.1080/00223980.2011.613875

Wang, J., Mann, F., Lloyd-Evans, B., Ma, R., & Johnson, S. (2018). Associations between loneliness and perceived social support and outcomes of mental health problems: A systematic review. *BMC Psychiatry*, *18*(1), 156. https://doi.org/10.1186/s12888-018-1736-5

Wang, N., Goel, S., Ibrahim, S., Badal, V. D., Depp, C., Bilal, E., Subbalakshmi, K., & Lee, E. (2024). Decoding loneliness: Can explainable AI help in understanding language differences in lonely older adults? *Psychiatry Research*, *339*, 116078. https://doi.org/10.1016/j.psychres.2024.116078

Warham, J. (1976). T. H. Marshall, Social Policy in the Twentieth Century, fourth revised edition, Hutchinson. University Library, London, 1975. 240 pp. £3.95, paper £1.95. *Journal of Social Policy*, *5*(2), 196–197. https://doi.org/10.1017/S0047279400022285

Weiss, R. (1975, April 15). *Loneliness: The Experience of Emotional and Social Isolation*. MIT Press.

Wenger, G. C., Davies, R., Shahtahmasebi, S., & Scott, A. (1996). Social Isolation and Loneliness in Old Age: Review and Model Refinement. *Ageing and Society*, *16*(3), 333–358. https://doi.org/10.1017/S0144686X00003457

Williams, A. J., McHale, C., Chow, C., Van Ry, R., & Cope, A. (2024, January 1). Chapter Nine - Systematic review of the associations between transport and loneliness. In J. S. Mindell & S. J. Watkins (Eds.), *Advances in Transport Policy and Planning* (pp. 283–342, Vol. 13). Academic Press. https://doi.org/10.1016/bs.atpp.2023.11.005

Wolf, J., Goerigk, S., Midderhoff, F., Burkhardt, G., Bühner, M., Köhler, S., Falkai, P., Jobst, A., Padberg, F., & Reinhard, M. A. (2025). Temporal interaction of suicidal ideations and behaviors with loneliness in persistent depressive disorder – a feasibility study using ecological momentary assessment. *European Archives of Psychiatry and Clinical Neuroscience*, *275*(4), 1253–1259. https://doi.org/10.1007/s00406-024-01931-8

Wongvorachan, T., He, S., & Bulut, O. (2023). A Comparison of Undersampling, Oversampling, and SMOTE Methods for Dealing with Imbalanced Classification in Educational Data Mining. *Information*, *14*(1), 54. https://doi.org/10.3390/info14010054

Wu, C., Barczyk, A. N., Craddock, R. C., Harari, G. M., Thomaz, E., Shumake, J. D., Beevers, C. G., Gosling, S. D., & Schnyer, D. M. (2021).

Improving prediction of real-time loneliness and companionship type using geosocial features of personal smartphone data. *Smart Health*, *20*, 100180. https://doi.org/10.1016/j.smhl.2021.100180

Wu, Z., & Penning, M. (2015). Immigration and loneliness in later life. *Ageing & Society*, *35*(1), 64–95. https://doi.org/10.1017/S0144686X13000470

Wynter, A. de. (2025, May 30). *If Eleanor Rigby Had Met ChatGPT: A Study on Loneliness in a Post-LLM World*. arXiv: 2412.01617 [cs]. https://doi.org/10.48550/arXiv.2412.01617

Xiong, M., & Xu, W. (2023). Association of relative deprivation with loneliness and its underlying mechanisms: Evidence from Chinese migrant children. *Frontiers in Psychology*, *14*. https://doi.org/10.3389/fpsyg.2023.1048164

Xu, X., Yao, B., Dong, Y., Gabriel, S., Yu, H., Hendler, J., Ghassemi, M., Dey, A. K., & Wang, D. (2024). Mental-LLM: Leveraging Large Language Models for Mental Health Prediction via Online Text Data. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, *8*(1), 1–32. https://doi.org/10.1145/3643540

Yadav, U., & Sharma, A. K. (2023). A novel automated depression detection technique using text transcript. *International Journal of Imaging Systems and Technology*, *33*(1), 108–122. https://doi.org/10.1002/ima.22793

Yarkoni, T., & Westfall, J. (2017). Choosing Prediction Over Explanation in Psychology: Lessons From Machine Learning. *Perspectives on Psychological Science*, *12*(6), 1100–1122. https://doi.org/10.1177/1745691617693393

Young, J., & Dryden, W. (2019). Single-session therapy – past and future: An interview. *British Journal of Guidance & Counselling*, *47*(5), 645–654. https://doi.org/10.1080/03069885.2019.1581129

Yusoff, M. S. B. (2019). ABC of Content Validation and Content Validity Index Calculation. *Education in Medicine Journal*, *11*(2), 49–54. https://doi.org/10.21315/eimj2019.11.2.6

Zagic, D., Wuthrich, V. M., Rapee, R. M., & Wolters, N. (2022). Interventions to improve social connections: A systematic review and meta-analysis. *Social Psychiatry and Psychiatric Epidemiology*, *57*(5), 885–906. https://doi.org/10.1007/s00127-021-02191-w

Zeberga, K., Attique, M., Shah, B., Ali, F., Jembre, Y. Z., & Chung, T.-S. (2022). A Novel Text Mining Approach for Mental Health Prediction Using Bi-LSTM and BERT Model (S. A. C. Bukhari, Ed.). *Computational Intelligence and Neuroscience*, *2022*, 1–18. https://doi.org/10.1155/2022/7893775

Zhang, H., & Firdaus, A. (2024). What Does Media Say about Mental Health: A Literature Review of Media Coverage on Mental Health. *Journalism and Media*, *5*(3), 967–979. https://doi.org/10.3390/journalmedia5030061

Appendix A

List of Abbreviations

ACTO - Association for Counselling and Therapy Online
Adult SWAN-OM - Adult Session Wants and Needs Outcome Measure
AI - Artificial Intelligence
AUC - Area Under the ROC Curve
BERT - Bidirectional Encoder Representations from Transformers
BPD - Borderline Personality Disorder
CBT - Cognitive Behavioural Therapy
CLS - Children's Loneliness Scale
CORE-OM - Clinical Outcomes in Routine Evaluation Outcome Measure
COVID-19 - Coronavirus Disease 2019
CTM - Contextualised Topic Model
CVI - Content Validity Index
DJG - De Jong Gierveld (Loneliness Scale)
DLS - Differential Loneliness Scale
DMCS - Department for Culture, Media and Sport
DMHP - Digital Mental Health Platform
EMA - Ecological Momentary Assessment
ESQ - End of Service Questionnaire
EUPD - Emotionally Unstable Personality Disorder
FI - Feature Importance
GAD-7 - Generalized Anxiety Disorder-7
GLA - Greater London Authority
GP - General Practitioner
I-CVI - Item-level Content Validity Index
IMD - Indices of Multiple Deprivation
K-10 - The Kessler Psychological Distress Scale
LIWC - Linguistic Inquiry Word Count
LLMs - Large Language Models
LoRA - Low-Rank Adaptation
LR - Logistic Regression
MCR - Model Class Reliance
ML - Machine Learning
MSOA - Middle Layer Super Output Areas
NHS - National Health Service
NLP - Natural Language Processing
NLTK - Natural Language Toolkit

OAAT - One-at-a-time
ONS - Office for National Statistics
PI - Permutation Importance
PIP - Personal Independence Payments
POS - Part of Speech
R-UCLA - Revised UCLA Loneliness Scale
RECS - Residential Energy Consumption Survey
RF - Random Forest
S-CVI - Scale-level Content Validity Index
SDQ - Strengths and Difficulties Questionnaire
SELSA - Social and Emotional Loneliness Scale for Adults
SEM - Structural Equation Modelling
SHAP - Shapley Additive exPlanations
SLS - Stigma of Loneliness Scale
SMOTE - Synthetic Minority Oversampling Technique
SST - Single Session Therapy
SU - Service User
SVM - Support Vector Machine
SWAN-OM - Session Wants and Needs Outcome Measure
SWEMWBS - Short Warwick-Edinburgh Mental Wellbeing Scale
TA - Thematic Analysis
TF-IDF - Term Frequency Inverse Document Frequency
UC - Universal Credit
UCLA - University of California, Los Angeles (Loneliness Scale)
XGBoost - Extreme Gradient Boosting
YP-CORE - Young Person's CORE

Appendix B

Study 3 Complete London Survey Questions (By Question Theme)

Question	Response Options
How would you describe your gender?	Male; Female; Non-binary; Prefer not to say
What range best describes your age group?	16 to 19; 20 to 24; 25 to 29; 30 to 34; 35 to 39; 40 to 44; 45 to 49; 50 to 54; 55 to 59; 60 to 64; 65 to 69; 70 to 74; 75 to 79; 80 or over
Do you have any physical or mental health conditions or illnesses that are limiting your day to day activities?	No; Yes; Prefer not to say
Which of the following best describes your household?	Living on my own (NO children or children have left home); Living on my own WITH children under 18; Living with other adult family members; Living with other adults that are non-family members; Living with partner/spouse (NO children or children have left home); Living with partner/spouse/older relative WITH children under 18

Table B.1: Demographics Questions

Question	Response Options
What is your employment status?	Working full-time; Working part-time; Unemployed; Retired; Not working- looking after house/children; Not working- long term sick or disabled; Student; Other
What is your annual household income before tax?	Less than £14,900 p.a.; £14,901- £24,300 p.a.; £24,301- £37,900 p.a.; £37,901- £58,900 p.a.; More than £58,900 p.a.; Prefer not to say

Table B.2: Employment and Income Questions

Question	Response Options
In general, how satisfied are you with your life?	1-10
Compared to others in my neighbourhood, I think my life overall is...	Better; Much better; Much worse; The same; Worse

Table B.3: Life Satisfaction Questions

Question	Response Options
How often do you feel that you lack companionship?	Hardly Ever or Never; Some of The Time; Often or Always
How often do you feel isolated from others or left out?	Hardly Ever or Never; Some of The Time; Often or Always
To what extent are you able to turn to friends and family for help when you need it?	Not at all; To some extent; To a large extent
Generally, I borrow things and exchange favours with my neighbours	Agree; Disagree

Table B.4: Social Connection Questions

Question	Response Options
In the past 12 months, did you get help obtaining food from any of the following?	
- Foodbank	TRUE; FALSE
- Neighbours	TRUE; FALSE
- Close family or friends	TRUE; FALSE
- Community or faith group	TRUE; FALSE
- None of the above	TRUE; FALSE
- Other	TRUE; FALSE

Table B.5: Support Systems Questions

USDA Food Security Survey Module	
Question	**Response Options**
We worried whether our food would run out before we got money to buy more	Often true; Never true; Sometimes true
The food that we bought just didn't last, and we didn't have money to get more	Often true; Never true; Sometimes true
We couldn't afford to eat balanced meals	Often true; Never true; Sometimes true
Did you or other adults in your household ever cut the size of your meals or skip meals because there wasn't enough money for food?	Yes; No
How often did this happen?	Almost every month; Only 1 or 2 months; Some months but not every month
Did you ever eat less than you felt you should because there wasn't enough money for food?	Yes; No
Were you ever hungry but didn't eat because there wasn't enough money for food?	Yes; No
Did you lose weight because there wasn't enough money for food?	Yes; No
Did you or other adults in your household ever not eat for a whole day because there wasn't enough money for food?	Yes; No
We relied on only a few kinds of low-cost food to feed our children because we were running out of money to buy food	Often true; Never true; Sometimes true
We couldn't feed our children a balanced meal, because we couldn't afford that	Often true; Never true; Sometimes true
The children were not eating enough because we just couldn't afford enough food	Often true; Never true; Sometimes true
Did you ever cut the size of any of the children's meals because there wasn't enough money for food?	Yes; No
Were the children ever hungry but you just couldn't afford more food?	Yes; No
Did any of the children ever not eat for a whole day because there wasn't enough money for food?	Yes; No

Table B.6: Food Security Questions (USDA Module)

Energy Security Questions	
Question	**Response Options**
Do you know the Energy Performance Certificate (EPC) rating for the house you currently live in?	A; B; C; D; E; F; G; Don't know
Do you use a prepayment or pay-as-you-go meter to pay for your energy usage?	Yes; No; Don't know
In the past year, how frequently did your household keep your home at a cold temperature that you felt was unsafe or unhealthy?	Never; Almost Every Month; Some months but not every month; Every 1 or 2 months
In the past year, how frequently did your household run behind on payments for energy bills, or receive a notice to disconnect?	Never; Almost Every Month; Some months but not every month; Every 1 or 2 months
In the last year, was there ever a time your household was unable to use your main source of heat because you could not afford to pay for gas or electricity?	Yes; No
About how many days over the past year has your household gone without heat because you could not afford to pay for gas or electricity?	0-356
In the last year, was there ever a time your household was unable to use your main source of heat because the equipment was broken, and you couldn't afford to pay to repair or replace the equipment?	Yes; No
In the past year, did anyone in your household need medical attention because your home was too cold?	Yes; No
In the past year, how often did you worry about making energy payments?	Never; Almost Every Month; Some months but not every month; Every 1 or 2 months
In the past year, how often did you worry about making rent/mortgage payments?	Never; Almost Every Month; Some months but not every month; Every 1 or 2 months
Consider your grocery shopping habits in the past 12 months. How often have you avoided food that requires cooking to reduce energy usage?	Never; Almost Every Month; Some months but not every month; Every 1 or 2 months

Table B.7: Energy Security Questions

Appendix C

LLM Prompt

The following prompt configuration was used for the LLM-based loneliness detection model:

System Prompt

```
You are an expert analysing social media for loneliness indicators.
You must respond with valid JSON only.
```

Rules:

1. Analyse only the post content provided
2. Output structured JSON with exact format shown
3. For lonely posts, select ONE label from EACH category
4. Provide brief, specific reasoning based on text evidence
5. No additional text outside the JSON structure

User Instruction Template

```
Analyse this post for loneliness expression:

Post:  "{row[text_column]}"
```

Category Labels:

- **Disclosure:** "Direct" (explicitly states loneliness), "Indirect" (implies loneliness)
- **Duration:** "Transient" (temporary), "Enduring" (long-term), "Ambiguous" (unclear), "NA" (not mentioned)
- **Context:** "Social" (lack of connections), "Physical" (isolation), "Somatic" (bodily feelings), "Romantic" (partnership), "NA" (no specific context)
- **Interpersonal:** "Romantic" (partner), "Friendship" (friends), "Family" (relatives), "Peers" (colleagues/classmates), "NA" (unspecified)
- **Interaction:** "Seeking Advice", "Providing Support", "Seeking Validation", "Reaching Out", "Non-Directed"

Required JSON Format

```
{
  "lonely": true/false,
  "reasoning": [
    "Primary evidence for loneliness determination",
    "Specific textual indicators or lack thereof"
  ],
  "categories": {
    "disclosure": "label_if_lonely_else_null",
    "duration": "label_if_lonely_else_null",
    "context": "label_if_lonely_else_null",
    "interpersonal": "label_if_lonely_else_null",
    "interaction": "label_if_lonely_else_null"
  }
}
```

Appendix D

LoRA Fine-tuning Configuration and Training Parameters

Table D.1: LoRA Fine-tuning Architecture Configuration

Parameter	Value	Description
Rank (r)	16	Controls the expressiveness of LoRA adapters; higher values increase model capacity but require more parameters
Alpha	32	Scales the contribution of LoRA updates relative to original weights; typically set to 2× the rank value
Dropout	0.1	Prevents overfitting by randomly zeroing LoRA layer outputs during training
Task Type	Causal Language Modelling	Defines the model's training objective for next-token prediction tasks

Table D.4: Reproducibility and Logging Configuration

Parameter	Value	Description
Random Seed	42	Ensures consistent results across training runs by controlling random number generation
Logging Frequency	Every 5 steps	Frequency of training metric recording for monitoring training progress and debugging

Table D.2: Training Configuration Parameters

Parameter	Value	Description
Batch Size (per device)	16	Number of samples processed simultaneously on each GPU; affects memory usage and training stability
Gradient Accumulation	4	Accumulates gradients across multiple forward passes before updating parameters; simulates larger batch sizes
Effective Batch Size	64	Combined effect of batch size and gradient accumulation; influences training dynamics and convergence
Learning Rate	5e-5	Controls the step size for parameter updates; balances training speed with stability
LR Scheduler	Cosine with restarts	Gradually reduces learning rate following cosine curve with periodic resets to escape local minima
Warmup Ratio	0.1	Gradually increases learning rate from zero during initial training to stabilise early optimisation
Weight Decay	0.01	Penalises large parameter values to prevent overfitting and improve generalisation
Maximum Steps	246	Defines the total number of optimisation steps for training completion

Table D.3: Optimisation Strategy and Computational Efficiency

Parameter	Value	Description
Optimiser	AdamW (8-bit)	Adaptive learning rate optimiser with weight decay correction and memory-efficient 8-bit precision
Precision	bfloat16	Reduces memory usage and increases training speed whilst maintaining numerical stability
Gradient Checkpointing	Enabled	Trades computation for memory by recomputing intermediate activations during backpropagation
Quantisation	4-bit	Reduces model memory footprint by representing weights with lower precision

Appendix E

Comprehensive Performance Evaluation of TF-IDF Based Text Classification Models

Table E.1: Comprehensive Performance Evaluation of TF-IDF Based Text Classification Models

Model	Test Set					Validation Set					Training Set				
	Acc	**Prec**	**Rec**	**F1**	**AUC**	**Acc**	**Prec**	**Rec**	**F1**	**AUC**	**Acc**	**Prec**	**Rec**	**F1**	**AUC**
Baseline	0.544	0.296	0.544	0.384	0.500	0.531	0.282	0.531	0.369	0.500	0.531	0.282	0.531	0.369	0.500
LR Simple	0.926	0.926	0.926	0.926	0.977	0.910	0.910	0.910	0.910	0.966	0.918	0.918	0.918	0.918	0.971
LR Thorough	**0.929**	**0.929**	**0.929**	**0.929**	**0.979**	**0.913**	**0.913**	**0.913**	**0.913**	**0.968**	**0.921**	**0.921**	**0.921**	**0.921**	**0.973**
SVM Simple	0.922	0.922	0.922	0.922	0.975	0.907	0.907	0.907	0.907	0.964	0.915	0.915	0.915	0.915	0.970
SVM Thorough	0.925	0.925	0.925	0.925	0.977	0.910	0.910	0.910	0.910	0.966	0.918	0.918	0.918	0.918	0.971
RF Simple	0.914	0.914	0.914	0.914	0.970	0.900	0.900	0.900	0.900	0.959	0.907	0.907	0.907	0.907	0.965
RF Thorough	0.917	0.917	0.917	0.917	0.972	0.903	0.903	0.903	0.903	0.961	0.910	0.910	0.910	0.910	0.967
XGB Simple	0.918	0.918	0.918	0.918	0.973	0.904	0.904	0.904	0.904	0.962	0.912	0.912	0.912	0.912	0.968
XGB Thorough	0.921	0.921	0.921	0.921	0.975	0.906	0.906	0.906	0.906	0.963	0.914	0.914	0.914	0.914	0.969

Table Description: This table presents a comprehensive comparison of TF-IDF based text classification models evaluated across training, validation, and test datasets. Models include a majority class baseline, Logistic Regression (LR), Support Vector Machine (SVM), Random Forest (RF), and Extreme Gradient Boosting (XGB), each implemented with both simple and thorough hyper-parameter configurations. Performance metrics include Accuracy (Acc), Precision (Prec), Recall (Rec), F1-score (F1), and Area Under the ROC Curve (AUC). **Bold values** indicate the highest performance achieved for each metric across all models.

Appendix F

LLM Reasoning for Posts Misclassified by TF-IDF Model

Table F.1: LLM Contextual Analysis of All Posts Misclassified by TF-IDF Model

ID	Content (Excerpt)	LLM Reasoning
73	"I agree. I am lonely BECAUSE i have no friends... For me loneliness is having no friends..."	Model error - no reasoning provided
3407	"exactly how I've been feeling ever since my boyfriend left me-he was my only friend and now I have no one..."	Explicit loneliness following breakup. Evidence of lacking companionship and emotional support.
2667	"we'll all be your friends! you're never alone"	Reassures others they are not alone, indicating concern for others rather than personal loneliness.
2049	"I feel empty and lonely all the time - even with people around me..."	Explicitly states feelings of loneliness despite being surrounded by people.
4077	"i feel the exact same as you. ur not alone"	Focuses on supporting another person. Suggests empathy rather than self-disclosure of loneliness.
9933	"I'm feeling the exact same as you you are not alone"	Reassures others and expresses empathy, indicating supportive intent rather than personal loneliness.
18760	"I feel the exact same too, your not alone.."	Provides reassurance and support rather than expressing personal loneliness.
30	"Though we are all surrounded by people, we often tend to feel lonely... So if you need someone to talk to, I'm here for you!"	Explicitly states feelings of loneliness. Mixed content combining personal experience with supportive messaging.
2610	"This is me but only when my other Friend isn't here, she always talks about her and makes me feel lonely..."	Explicitly states feelings of loneliness in specific social situations triggered by interpersonal dynamics.
18943	"Same your not alone."	Reassures the listener rather than expressing loneliness.
11044	"Your not alone"	Aims to comfort rather than express loneliness. Provides reassurance indicating positivity.
19957	"Ur not alone x"	Model error - no reasoning provided
20743	"I have Arachnophobia and Claustrophobia too. So ur not alone."	Discloses personal fears. Personal vulnerability shared in supportive context.
5834	"I do, your not alone!"	Reassures others rather than expressing loneliness. Provides encouragement and support.
5696	"you're not alone"	Model error - no reasoning provided
18391	"same. Your not alone"	Does not express or imply loneliness. Provides reassurance rather than emotional distress.
17889	"I feel the same your not alone"	Focuses on comforting someone else. Uses empathetic language directed toward another party.
4042	"I do too- you're not alone. :]"	Does not express personal loneliness but offers reassurance and support.
22483	"Same. You're not alone."	Reassures others rather than expressing personal loneliness.
16686	"You are not alone"	Provides encouragement rather than expressing personal loneliness.

Appendix G

Evidence of Subreddit Labels Present in the Original "Many Ways to Be Lonely Fine Grained Characterization of Loneliness and Its Potential Changes in COVID 19" Paper

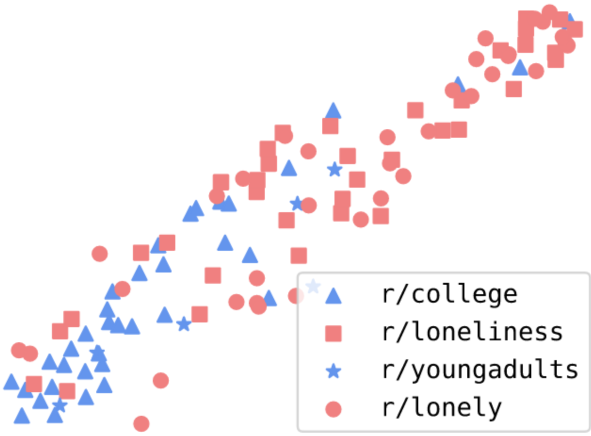

Figure G.1: *Figure 6: "t-SNE embedding of the HDLN model predicted lonely posts across different subreddits". Jiang et al. (2022) p.411*