Computational Analysis of Mental Health Discourse Among Young Irish Adults (2021–2024)

“A Big Data Analytics Study Using Social Media and Search Engine Data”

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M.Sc. in Computing in Big Data Analytics 2025



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“A Big Data Analytics Study Using Social Media and Search Engine Data”

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*Arna chur isteach chuig Ollscoil Teicneolaiochta an Atlantaigh* August 2025

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Without the data and platforms, this study could not have been conducted. I also want to pay respect to **Reddit**, which can facilitate anonymous conversations about mental health as it is crucial to make inferences about the mental health trends in the population. I would also like to thank **Google Trends** because they offer publicly available data on search behavior allowing the cross platform validation aspect of this experiment.

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# Abstract

This dissertation applies Big Data Analytics to examine mental health discourse among young Irish adults in the post-COVID period (2019–2024). A total of 8,571 Reddit posts were analysed using the transformer-based GoEmotions model for multi-label emotion classification.

Reliability was strengthened through a probability threshold (≥0.30) and keyword validation, with outputs cross-validated against Google Trends indices for external consistency.

The findings highlight an anxiety–depression substitution pattern. Depression-related discourse steadily declined, while anxiety nearly doubled, with seasonal peaks around examination months and higher depression in winter. Community analysis showed that university forums contained disproportionately high anxiety compared to general youth communities, while depression was more prevalent outside student settings.

Cross-platform validation demonstrated alignment between Reddit discourse indicators and Irish search behaviour, with trends closely tracking exam stress and counselling-related queries.

Overall, the study demonstrates how privacy-preserving NLP pipelines can generate scalable, reproducible insights into youth mental health. By integrating discourse analysis with behavioural validation, it advances Big Data Analytics methodology while contributing culturally relevant evidence to support digital mental health monitoring in Ireland.

# Acronyms

|  |  |  |
| --- | --- | --- |
| **Acronym** | **Definition** | **First Page Used** |
| ML | Machine Learning | 1 |
| NLP | Natural Language Processing | 1 |
| RQ | Research Question | 3 |
| LLM | Large Language Model | 18 |
| API | Application Programming Interface | 22 |
| PRAW | Python Reddit API Wrapper | 22 |
| BERT | Bidirectional Encoder Representations from Transformers | 31 |
| STL | Seasonal-Trend Decomposition using Loess | 31 |
| GDPR | General Data Protection Regulation | 33 |
| CI | Confidence Interval | 36 |
| CSV | Comma-Separated Values | 38 |

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# Chapter 1: Introduction

The COVID-19 pandemic reshaped education, employment, and social life in Ireland, exposing young adults to sustained psychological stress. Traditional surveillance methods such as surveys and clinical assessments remain valuable, but they are costly, infrequent, and slow to detect change. By contrast, digital platforms provide continuous streams of discourse in which individuals share experiences and coping strategies. Converting these streams into evidence requires methods that account for cultural context, linguistic variation, and temporal dynamics. Generic sentiment tools are not well suited to these demands, often overlooking critical nuances in mental health expression.

This dissertation develops a Big Data Analytics framework that combines transformer-based natural language processing (NLP) with cross-platform validation. Using authenticated collection and structured pre-processing, the study analyses 8,571 public Reddit posts gathered from 2019 to 2024, with primary focus on the post-COVID period (2021–2024). Posts were filtered for English and for Irish relevance, and were stratified into university and general youth communities. A transformer-based GoEmotions classifier was implemented for multi-label emotion detection and mapped transparently into six analytical groups: depressive symptoms, anxiety and stress, positive mood, hope and optimism, social connection, and anger and frustration. Monthly indicators were derived to quantify discourse trends, which were validated against Ireland-based Google Trends indices. The analysis is conducted at an aggregate level and does not infer clinical diagnoses.

The central aim is to examine whether computational analytics can reliably detect and validate mental health discourse patterns among young Irish adults. The contribution is twofold. Methodologically, the study demonstrates how unstructured social media text can be transformed into validated indicators using modern NLP and statistical testing. Substantively, it provides evidence of post-COVID shifts in anxiety- and depression-related discourse in an Irish context, with particular attention to academic calendar effects and community differences.

## 1.2 Background and Context

The study is situated in the post-pandemic realities of Ireland, where social, educational, and economic disruptions left lasting effects on young adults’ wellbeing. Digital platforms have become important venues for expressing distress and seeking support, while advances in computational methods now make it possible to examine these expressions at scale.

### 1.2.1 Ireland after the pandemic disaster

The years 2021 to 2024 were not a simple return to pre-pandemic routines. Instead, they marked a period of adaptation during which universities reopened, workplaces adjusted, and social life resumed under new constraints. For young adults, this transition involved navigating uncertainty around studies, finances, and career prospects. Anxiety related to performance and reintegration often intensified, while depressive expression evolved as social connections and activities were gradually restored. This study does not assume outcomes in advance but develops a pipeline capable of detecting such patterns if present.

### 1.2.2 Digital spaces as mental health communities

Reddit provides a semi-anonymous environment that facilitates open discussion of sensitive issues. Irish-focused and student communities coexist alongside global mental health spaces, creating an intersection between local and international perspectives. This research does not treat Reddit as representative of all young adults in Ireland, but as a platform where relevant discourse occurs. The analysis therefore focuses on aggregates of posts over time rather than individual users.

### 1.2.3 Advances in analysing online emotional expression

Modern NLP models allow for multi-label emotion detection, moving beyond simplistic positive–negative sentiment analysis. The GoEmotions model, trained on Reddit data, classifies text into twenty-seven labels. For this study, these labels were systematically grouped into six categories relevant to mental health. Confidence thresholds were applied to ensure reliability, while spot checks confirmed cultural appropriateness for Irish English. Full technical details are provided in Chapter 3.

## 1.3 Problem Statement

Although computational approaches to mental health analysis have advanced, current methods still fall short in providing reliable large-scale monitoring. Many studies reduce discourse to positive or negative sentiment, which fails to capture the complexity of mental health expression and results in the loss of critical signals (Chancellor & De Choudhury, 2020). Emotion classification models are available, but are often applied without considering cultural or institutional context. This weakens their relevance, as the way young adults express stress and resilience is shaped by local environments such as academic calendars and support systems (O’Connor et al., 2021).

Another limitation lies in the temporal and structural design of prior research. Much of the existing literature is based on short-term or event-driven datasets, providing only snapshots rather than multi-year perspectives. Similarly, reliance on a single platform narrows validity, since discourse on social media and behavioural data from search engines reflect different but complementary signals of wellbeing. Few studies integrate these sources into cross-platform pipelines, leaving outputs open to bias and limiting generalisability.

This dissertation responds to these gaps by developing a Big Data Analytics framework that combines natural language processing, multi-label emotion classification, longitudinal modelling, and cross-platform validation. The framework is designed to improve accuracy, cultural relevance, and reproducibility, providing stronger evidence for understanding the mental health discourse of young Irish adults between 2021 and 2024.

## 1.4 Research Question

The study is guided by two core questions:

**Primary Research Question**

To what extent can a Big Data NLP framework employing multi-label emotion classification move beyond sentiment polarity to more accurately capture the nuanced complexity of mental health discourse among young Irish adults?

**Secondary Research Question**

Does cross-platform validation, merging social media datasets with search engine trends, contribute to improved accuracy and resilience in digital mental health surveillance frameworks?

Choice 2

**Primary Research Question**

Can a Big Data NLP framework that integrates multi-label emotion classification provide deeper insights into mental health discourse among young Irish adults than sentiment polarity alone?

**Secondary Research Question**

Can cross-platform validation, combining social media data with search engine trends, enhance the accuracy and robustness of digital mental health surveillance frameworks?

## 1.6 Aim, Objectives, Scope and Limitations

The aim of this dissertation is to design and evaluate a Big Data Analytics framework that applies multi-label natural language processing to capture the complexity of mental health discourse among young Irish adults, and to validate its outputs against independent behavioural evidence. This reflects the primary research question, which investigates whether advanced emotion classification can move beyond sentiment polarity, and the secondary question, which examines whether cross-platform validation enhances accuracy and robustness.

To achieve this aim, the study collects Reddit posts from Irish youth-focused communities, applies the GoEmotions model to categorise emotions into relevant mental health categories, and generates indicators suitable for longitudinal analysis. Temporal trends in anxiety- and depression-related discourse are examined and compared between student-focused and general communities. These indicators are then validated against Ireland-specific search engine trends to assess reliability across platforms. Transparency and reproducibility are ensured through clear documentation of processes and visual presentation of outputs.

The scope of the dissertation is limited to English-language discourse in Irish Reddit communities between January 2019 and December 2024, with the main analytical focus on the years 2021 to 2024. Search engine data is used solely for validation and not as a primary source. Several limitations are recognised. Reddit users do not represent all young adults in Ireland, and the cultures of subreddits shape how issues are expressed. Geographic signals are approximate, and pre-processing choices may exclude some nuance. Emotion detection is sensitive to thresholds and linguistic variation, while monthly aggregation smooths short-term fluctuations. Correlations with search engine data indicate contemporaneous associations rather than causal relationships.

## 1.7 Significance of the Study

This study is significant because it addresses the lack of real-time, culturally sensitive monitoring of population mental health in Ireland. Young adults frequently turn to digital platforms rather than formal services to express their concerns, making online discourse a valuable but underused resource for public-health surveillance. The project contributes to academic research by demonstrating how transformer-based NLP models and fine-grained emotion classification can be applied to discourse in a specific cultural setting, extending current methodological practice. It also demonstrates how cross-platform validation can enhance the robustness of computational results, thereby reducing the risk of bias associated with single-platform studies.

In practical terms, the framework provides a means to generate timely evidence that informs public health decision-making. For example, identifying peaks in anxiety-related discussions within student communities could help universities target support services more effectively. Detecting seasonal variations in emotional expression could also inform broader resource allocation across the health system. By embedding privacy-by-design principles and using anonymisation techniques, the study demonstrates that it is possible to balance the need for population-level insights with the ethical requirement to protect individual confidentiality. In this way, the research makes both a methodological contribution to computational health analytics and a practical tool for more responsive mental health policy.

## 1.8 Conclusion

This chapter outlined the study’s motivation, problem statement, research questions, objectives, and significance. It situated the work within the post-COVID context of Ireland and emphasised the value of combining NLP with behavioural validation. The foundations presented here lead directly to Chapter 2, which reviews existing literature on digital mental health monitoring, emotion classification, and computational approaches.

## 1.9 Report Outline

The dissertation is organised into five chapters. Chapter 2 reviews the literature on traditional and computational approaches to mental health surveillance, including advances in NLP and emotion classification systems. Chapter 3 presents the Design and Implementation, describing the CRISP-DM framework, data collection, pre-processing, model development, validation strategies, and ethical considerations. Chapter 4 details the implementation of the proposed framework, including dataset preparation, model training, statistical evaluation, and development of the analytical interface. Chapter 5 presents the results and analysis, focusing on model performance, temporal trends, and cross-platform validation. Finally, Chapter 6 concludes the study, summarising the findings, discussing their implications for public-health practice, identifying limitations, and suggesting directions for future research.

Scope note: Findings in later chapters reflect the aggregated behaviour of Reddit users and Ireland-based search interest within the periods studied. They are not intended to represent the entire Irish population and should be read within the constraints of the data sources and methods described here.

# Chapter 2: Literature Review

This chapter provides a comprehensive review of the literature underpinning the analysis of digital mental-health discourse following the COVID-19 pandemic. It frames the research within both global and Irish mental-health contexts, and critically evaluates methodological and theoretical perspectives pertinent to computational studies. Building directly on Chapter 1, this review traces the development of current knowledge, identifies persistent limitations, and discusses how advanced techniques in natural language processing (NLP) and cross-platform validation can address these unresolved issues.

## 2.1 COVID-19 and Mental Health

COVID-19 precipitated a dual crisis, combining a major public health threat with a dramatic rise in psychological distress worldwide. Among the groups most affected, young adults faced increased rates of anxiety, depression, and interruptions to key developmental processes, including education and early employment (Xiong et al., 2020; Salari et al., 2020). Although the short-term psychological effects are well documented, the longer-term processes of adaptation and recovery, especially within Ireland, are less thoroughly explored.

### 2.1.1 Acute Impacts and Early Adaptation

During the onset of the pandemic, sudden disruptions to education, work, and social life were widespread. Students and individuals at the start of their careers experienced notable rises in depressive symptoms, anxiety, and suicidal thoughts (Copeland et al., 2021). Additionally, increased substance use and sleep disturbances were prevalent, often intensified by extended periods of isolation and uncertainty (Brooks et al., 2020; Charles et al., 2021). These pressures revealed systemic weaknesses in both university and healthcare infrastructures.

Available evidence suggests that adaptation processes began early in the pandemic but progressed unevenly among young adults. While some individuals turned to digital counselling or online peer-support networks, others withdrew from formal support structures. Cross-sectional studies provide limited insight into resilience due to methodological challenges, including recall bias, delayed reporting, and the exclusion of digitally disconnected populations (Panchal et al., 2021). Computationally, the shift from acute distress to gradual adaptation highlights the shortcomings of traditional survey approaches and emphasises the necessity for scalable analytical tools that can monitor temporal changes, seasonal effects, and emergent discourse in real time.

### 2.1.2 Long-term Implications

As emergency restrictions lifted, discourse moved towards questioning whether the mental-health impacts of the pandemic were transitory or signified more enduring generational effects. Longitudinal research presents mixed findings, with evidence of increased openness regarding mental health issues online alongside growing skepticism toward established clinical pathways (Chen et al., 2021; Goldberg et al., 2022). Peer-oriented platforms such as Reddit have emerged as key venues for sharing experiences and seeking support, sometimes replacing traditional professional channels (Naslund et al., 2020). The challenge of social reintegration after extensive isolation has introduced additional stressors for university students, indicating that the pandemic’s influence persists beyond its acute stages.

However, there is ongoing debate as to whether these patterns represent short-term adaptation or deeper structural change in how young adults express psychological distress. Differentiating between cyclical recovery and lasting transformation requires longitudinal, computational monitoring that can capture adaptation over extended periods. Techniques such as change-point detection and lag correlation, particularly when validated with behavioural datasets, are especially suitable for addressing this analytical challenge.

These unresolved questions highlight the value of digital platforms as robust data sources. With careful methodological safeguards, online discourse provides a window into real-time shifts in population well-being. The subsequent section evaluates the application of social media and natural language processing (NLP) in mental health research and discusses the remaining challenges.

## 2.2 Digital Mental Health and Social Media

If the pandemic exposed vulnerabilities in young adults’ well-being, it also highlighted the role of digital platforms as primary arenas for articulating distress. Unlike retrospective surveys, which capture snapshots at intervals, social media records discourse continuously and in near real time. This provides opportunities for scalable population-level monitoring, but also raises challenges of representativeness, domain adaptation, and ethical responsibility.

### 2.2.1 Social Media as Data

Social platforms grant researchers large-scale access to spontaneous expressions of psychological states. Reddit is especially relevant due to its semi-anonymous design, which encourages disclosures less common on identity-linked networks, such as Facebook (Low et al., 2020). Prior studies show that emotional expression on Reddit correlates with survey or clinical measures, lending some external validity (Reece et al., 2017; Eichstaedt et al., 2018). Nevertheless, much of the current research has concentrated on identifying risks at the individual level, for example, suicidal ideation, rather than on modelling discourse patterns at the aggregate level over time or across different subgroups. This focus on individuals restricts insight into wider cultural or generational changes, which are central to this study.

While the availability of digital traces is considerable, their analytical value depends heavily on the sophistication of the computational methods applied. The evolution of natural language processing (NLP) has expanded the scope of what can be inferred from such data.

### 2.2.2 NLP for Mental-Health Discourse

Early lexicon-based sentiment approaches lacked the capacity to handle ambiguity, sarcasm, or idiomatic phrasing, leading to frequent misclassification. Transformer-based architectures, such as BERT, have improved contextual modelling by learning dependencies across entire sequences (Devlin et al., 2019; Rogers et al., 2020). Emotion taxonomies, such as GoEmotions, extended analysis beyond polarity, enabling classification into over 25 nuanced affective states (Demszky et al., 2020). Such granularity matters when differentiating between stress, anxiety, hopelessness, or sadness.

Nevertheless, portability issues remain. Most models are trained on American English corpora, creating risks of domain shift when applied to Irish English, where idiomatic markers and indirect phrasing may alter meaning (Benton et al., 2017). Without domain adaptation, results risk systematic misclassification. For this reason, cultural and linguistic calibration is a methodological necessity, not an optional refinement, for computational research in this field.

Even where improved models are deployed, outputs cannot be assumed to be accurate unless validated against external behavioural indicators. This has driven a turn toward cross-platform validation and cautious forms of population-level monitoring.

### 2.2.3 Cross-Platform Validation and Surveillance Potential

One persistent methodological question is whether online discourse reflects genuine psychological states or merely platform-specific artefacts. Cross-platform validation provides partial answers by aligning social media signals with independent indicators such as Google Trends (Ayers et al., 2013). For instance, spikes in anxiety-related posts often coincide with increased searches for mental-health services, though the causal sequence remains contested (Cavazos-Rehg et al., 2018). These behavioral anchors enhance interpretability but do not eliminate biases, as online populations tend to skew younger, more male, and more technologically literate than the general population.

At the same time, attempts to formalise these methods into real-time surveillance systems raise governance dilemmas. While such tools could help detect emergent crises faster than traditional surveys, they risk amplifying transient events, reproducing demographic biases, and infringing on user privacy. Ethical safeguards, transparency in algorithmic design, and privacy-by-design principles are therefore prerequisites for the responsible application of these technologies in practice or policy contexts.

Taken together, the literature suggests that social media platforms provide valuable yet imperfect indicators of population well-being. Their utility depends on culturally adapted NLP pipelines, external validation across multiple data sources, and rigorous governance. The next section turns to the Irish context, where healthcare structures, cultural norms, and socioeconomic pressures interact to shape how mental health is experienced and expressed.

## 2.3 The Irish Mental Health Context

Understanding the Irish context is essential for interpreting digital mental health discourse. While international research outlines broad pandemic impacts, national healthcare structures, cultural norms, and socioeconomic pressures strongly mediate how young adults in Ireland experience and express psychological distress. This section first reviews the mental health system before and during the COVID-19 pandemic, and then considers how university pressures, cultural attitudes, and economic conditions shaped the discourse.

### 2.3.1 Ireland's Mental Health System Before and During COVID-19

Ireland’s mental-health services were undergoing reform prior to COVID-19, with policy emphasising community-based care and early intervention (Higgins et al., 2016). The pandemic accelerated digital counselling and telepsychiatry, but utilisation patterns revealed imbalances. Anxiety-related presentations rose sharply, while depression-oriented services grew more modestly (Mental Health Commission, 2022). This mismatch suggested that existing treatment models were poorly aligned with shifting needs. For computational studies, these service gaps are important: they influence which conditions become most visible in digital discourse and underscore the need for population-level monitoring beyond clinical pathways.

### 2.3.2 University, Cultural, and Economic Modulators

Irish university students faced distinctive challenges during and after the pandemic. Surveys already indicated above-average psychological distress compared to European peers (Deasy et al., 2014). The abrupt shift to online learning, loss of campus life, and later anxieties about reintegration heightened stress, isolation, and uncertainty (Union of Students in Ireland, 2022; Irish Universities Association, 2023). Such dynamics make students a particularly relevant subgroup for digital discourse analysis, where academic calendars and peer norms leave detectable temporal patterns.

Cultural factors also shape how distress is expressed and interpreted. While stigma has declined, especially among younger cohorts, traditional values of resilience and communal solidarity still influence disclosure norms (Barron et al., 2021; McMahon et al., 2020). Religion’s role has weakened, yet linguistic traces of older attitudes persist in Irish-English idioms (Inglis, 2014; Walsh & McMahon, 2018). For NLP models, this raises domain-adaptation challenges: classifiers trained on American or British corpora may misclassify culturally specific expressions.

Economic pressures further compound these influences. Young adults were disproportionately affected by job losses in the hospitality and tourism sectors (CSO, 2021), while the housing crisis limited their independence and future planning options (Housing Agency, 2022). Rural–urban divides also restricted access to both digital and in-person services (Irish Rural Link, 2021). Together, these systemic, cultural, and economic modulators created conditions in which online platforms served as both outlets for expression and substitutes for unavailable supports.

Because Irish discourse is shaped simultaneously by health system dynamics, cultural values, and economic constraints, computational approaches must be carefully adapted to the local context. The next section reviews methodological frameworks in digital mental-health research, highlighting their strengths, limitations, and relevance to this dissertation.

## 2.4 Methodological Approaches in Digital Mental Health Research

The field of digital mental-health research is marked by rapid methodological innovation, but challenges remain in balancing computational sophistication with cultural sensitivity and ethical responsibility. Four areas are particularly relevant: emotion classification, validation strategies, temporal analysis, and cross-platform integration.

### 2.4.1 Emotion Classification in Digital Text

Early lexicon-based sentiment methods relied on static dictionaries, which proved limited in handling sarcasm, idiomatic expressions, and multi-word phrases (Mohammad & Turney, 2013). Machine learning models, and later transformer-based architectures such as BERT, introduced contextual awareness by modelling sequential dependencies (Devlin et al., 2019; Rogers et al., 2020). More recent tools, such as GoEmotions, allow classification into over 25 discrete affective states, extending analysis beyond simple polarity (Demszky et al., 2020). This granularity is critical for mental health research, where distinguishing between anxiety, stress, and hopelessness can reshape interpretations of population wellbeing. Nevertheless, challenges of domain adaptation remain, as models trained on US corpora may not capture Irish-English usage without retraining or fine-tuning.

### 2.4.2 Validation Strategies

Validation is central to determining whether computational models capture meaningful constructs rather than artefacts of training data. While traditional metrics such as precision, recall, and F1-score are necessary, they are not sufficient. Increasingly, studies include expert annotation, with inter-annotator agreement ensuring reliability (Resnik et al., 2015). Behavioural validation, often using Google Trends or service-utilisation data, provides external anchors (Eichstaedt et al., 2018). Triangulating multiple datasets can reduce the risk of platform bias, but such methods are often resource-intensive. The methodological challenge of balancing scalability and depth remains a central issue in applied NLP for mental health.

### 2.4.3 Temporal Analysis of Social Data

Analysing discourse over time introduces additional complexity. Temporal drift in language, seasonal cycles such as exam stress or winter affective patterns, and external shocks like policy changes or public-health campaigns can all distort observed trends (Coppersmith et al., 2018). Platform evolution, including algorithm updates or changes in moderation policy, may also create artefacts that resemble psychological shifts (Chandrasekharan et al., 2017). Statistical techniques, such as lag correlation, time-series decomposition, and change-point detection, are increasingly used to distinguish genuine mental-health signals from noise. However, questions of causality remain unresolved, as correlations can only indicate associations, not underlying mechanisms. For this reason, computational results must be interpreted cautiously.

### 2.4.4 Cross-Platform Integration

To strengthen external validity, researchers increasingly combine discourse analysis with behavioural signals. Google Trends has been widely used, with spikes in searches for “anxiety” or “depression” often paralleling online discussions of the same terms (Ayers et al., 2013; Cavazos-Rehg et al., 2018). This alignment bolsters interpretability but does not resolve questions of causal sequencing. It remains unclear whether online conversations precede behavioural searches, follow them, or simply co-occur. Techniques such as lag analysis and Granger causality testing provide partial answers, although the findings remain sensitive to model assumptions and temporal granularity.

### 2.4.5 Ethical Note and Forward Reference

Ethical issues cut across all methodological stages, from data collection to analysis and interpretation. Concerns about consent, anonymisation, and governance are particularly acute in mental-health contexts. These are examined in detail in Section 2.7; here it suffices to note that scalability must be balanced with privacy-by-design safeguards.

Despite advances in classification, validation, and integration, persistent gaps remain. Current approaches often truncate timelines, rely on corpora that are not adapted to Irish English, and struggle with interpretability. Section 2.5, therefore, consolidates these limitations into explicit research gaps and outlines how this dissertation is positioned to address them.

## 2.5 Research Gaps and Study Positioning

Despite the rapid growth of digital mental health research, several critical gaps limit both theoretical understanding and methodological robustness. Addressing these is essential for positioning the present study, particularly in the Irish post-pandemic context.

### 2.5.1 Identified Critical Research Gaps

To structure these limitations clearly, the following subsections outline the principal research gaps, beginning with temporal scope before moving through cultural, methodological, and validation concerns.

#### 2.5.1.1 Temporal Scope

Most longitudinal studies concluded by early 2022, leaving adaptation and recovery phases underexplored (Robinson et al., 2022; Aknin et al., 2022). This truncation creates uncertainty: are observed changes in young adults’ mental health short-lived artefacts of crisis, or enduring cohort effects? Without computational tracking across the 2019–2024 horizon, this distinction remains ambiguous. Events such as delayed campus reopening, labour-market restructuring, and shifting digital norms in 2023–2024 were still reshaping wellbeing but remain undocumented.

#### 2.5.1.2 Cultural and Geographic Specificity

Much of the computational literature relies on American or British corpora with minimal domain adaptation. In Ireland, cultural idioms, socioeconomic pressures, and healthcare structures play a significant role in shaping how distress is disclosed and framed (Benton et al., 2017). Using NLP models that are not adapted to this context can result in systematic misclassification, especially where Irish English features indirect phrasing or unique idiomatic expressions. This limitation highlights the methodological necessity of training or fine-tuning transformer-based models for local discourse.

#### 2.5.1.4 Methodological Integration

Social media discourse and behavioural validation (e.g., Google Trends) are often studied in isolation, leaving results vulnerable to platform artefacts. Many analyses rely on static correlations without testing lag structures, directional causality, or temporal drift. Without such integration, it remains unclear whether online discourse precedes behavioural change, mirrors it, or diverges. Incorporating techniques such as lag correlation, Granger causality, and cross-platform validation is therefore critical if online signals are to be treated as early indicators

#### 2.5.1.5 Community-Specific Dynamics

Most research treats social media users as homogeneous populations. For instance, university students may exhibit distinctive discourse patterns linked to academic calendars, financial pressures, or cultural contexts. Without stratified analysis, subgroup dynamics risk being obscured in aggregate modelling, reducing both interpretive clarity and the usefulness of findings for targeted interventions.

#### 2.5.1.6 Validation and Interpretability

Although emotion-classification systems such as BERT or GoEmotions achieve high benchmark accuracy, their portability to Irish English, local slang, and hybrid registers remains insufficiently tested (Guntuku et al., 2019). Additionally, deep learning presents challenges for interpretability. For computational findings to be accepted in academic and policy contexts, it is essential to implement transparent validation procedures that include expert annotation, inter-annotator agreement, keyword checks, and tests for temporal consistency.

### 2.5.2 Study Positioning and Novel Contributions

This dissertation addresses these limitations directly. By extending analysis through the end of 2024, it captures a full cycle of post-pandemic adaptation. It foregrounds the Irish context by adapting transformer-based NLP tools to local idioms and cultural references.

Methodologically, it integrates Reddit discourse with Google Trends search activity, moving beyond static correlations to assess temporal alignment and lag effects. This design strengthens inferences about whether online discussions precede, reflect, or diverge from offline behaviour.

The study also undertakes a subgroup analysis, contrasting university forums with broader Irish subreddits, thereby exposing dynamics that are masked in aggregate datasets. Finally, it implements a validation framework that combines expert annotation, inter-annotator agreement, and temporal consistency testing, enhancing both accuracy and interpretability.

Taken together, these contributions position the dissertation at the intersection of computational linguistics, behavioural validation, and cultural specificity. By addressing temporal, methodological, and contextual gaps, it offers both empirical insight and a replicable framework for future digital mental health research.

## 2.6 Theoretical Frameworks in Digital Mental Health Research

Identifying research gaps is only part of the task; studies also require theoretical perspectives that explain why digital discourse emerges as it does. This section outlines four frameworks: social support, self-disclosure, uses and gratifications, and stigma, each of which contextualises online mental health expression and links directly to the computational measures applied in this dissertation.

### 2.6.1 Social Support Theory in Digital Environments

Social Support Theory distinguishes emotional, informational, instrumental, and appraisal support (Cohen & Wills, 1985). On Reddit, these forms of support are often expressed through reply depth, advice-giving, or expressions of empathy (Naslund et al., 2016). Computationally, they can be proxied by comment chains, classifier outputs identifying reassurance versus neutral dialogue, or interaction density. Algorithms must be cautious, however, as irony and sarcasm can mimic supportive language (Rains & Young, 2009).

### 2.6.2 Self-Disclosure Theory and Digital Mental Health Expression

Self-Disclosure Theory holds that people commonly reveal personal information gradually as trust develops (Altman & Taylor, 1973). Online anonymity alters this trajectory, enabling rapid and detailed disclosure (Suler, 2004). From a computational standpoint, disclosure is detectable through the use of first-person pronouns, narrative length, and explicit mentions of personal struggles. These markers, however, do not capture underlying motivation, whether empathy-seeking, validation, or normalisation (Barak & Gluck-Ofri, 2007).

### 2.6.3 Uses and Gratifications Theory in Mental Health Contexts

Uses and Gratifications Theory explains why individuals choose particular platforms (Katz et al., 1973). Reddit offers informational and community gratifications, while other platforms may emphasise identity signalling or affective release (Burke & Kraut, 2016). Computationally, subreddit choice, posting frequency, and topic clustering serve as proxies for these gratifications, and cross-platform comparisons must account for such differences.

### 2.6.4 Stigma Theory and Digital Mental Health Discourse

Stigma Theory emphasises the impact of mental illness on identity and disclosure (Goffman, 1963). Anonymity can reduce stigma barriers, facilitating open discussion (Berger et al., 2005), but trolling and digital permanence introduce new risks (Houghton & Joinson, 2010). Computational markers, such as anonymity cues, lexical hedging, and humour detection, help identify posts where stigma influences expression.

Together, these frameworks guide both interpretation and feature selection, ensuring that computational signals related to language, time patterns, and interaction are grounded in established behavioural theory.

## 2.7 Methodological Considerations and Limitations

Although theoretical frameworks add interpretive depth, methodological constraints continue to influence the reliability and validity of digital mental health findings. Two clusters of limitations stand out: representativeness and temporal validity, as well as the challenges of validation and ethics.

### 2.7.1 Representativeness and Temporal Validity

Social media users do not accurately represent the general public. Reddit users tend to be younger, male, and technologically literate, which creates a demographic bias (Barthel et al., 2016; Mellon & Prosser, 2017). Self-selection further narrows representativeness: those willing to disclose online may differ systematically from those who remain silent (Ernala et al., 2019). Cultural transferability is also limited, as models trained on American or British corpora may misclassify idiomatic or indirect Irish-English phrasing (Benton et al., 2017).

Temporal factors complicate analysis. Algorithmic updates, moderation policies, and interface redesigns can generate artefacts (Chandrasekharan et al., 2017). Seasonal cycles such as exams or holidays also produce predictable spikes in stress-related discourse (Coppersmith et al., 2018). Without accounting for temporal drift, true cohort effects may be conflated with platform dynamics.

### 2.7.2 Validation and Ethical Constraints

Validation remains difficult because gold-standard clinical labels are scarce and costly. While inter-annotator agreement and triangulation with behavioural indicators (e.g., Google Trends) improve construct validity, these approaches are resource-intensive (Resnik et al., 2015; Eichstaedt et al., 2018). Interpretability is another concern: deep learning models may classify accurately but provide little transparency, making it uncertain whether they align with theoretical constructs.

Ethical considerations compound these challenges. Although posts are public, users may not anticipate their aggregation for research (Conway, 2014). Privacy-by-design safeguards, robust anonymisation, and governance protocols are therefore essential (Benton et al., 2019). Findings may also inform public health or platform policy, creating downstream risks if signals are misinterpreted.

Taken together, these constraints underscore that digital mental health findings remain probabilistic rather than definitive. They highlight the need for future research to refine methods while incorporating robust ethical and governance standards.

## 2.8 Future Directions and Emerging Trends

The literature not only documents what has been achieved but also highlights areas where digital mental health research is likely to evolve. Three domains stand out: technological innovation, methodological standardisation, and the translation of findings into policy and practice.

### 2.8.1 Technological Advances and Opportunities

Rapid progress in transformer-based NLP, large language models, and multimodal analysis is expanding the capabilities of extracting information from digital traces (Rogers et al., 2020). Beyond text, signals such as emojis, images, or posting rhythms provide richer proxies of well-being. Real-time monitoring systems capable of detecting sudden shifts in discourse are emerging (De Choudhury et al., 2016). Yet increased sensitivity intensifies concerns around governance and user privacy. For students and young adults, especially, monitoring may feel intrusive unless it is underpinned by strong ethical frameworks.

### 2.8.2 Methodological Innovations and Standards

Current studies often rely on fragmented datasets and heterogeneous evaluation metrics, which hinder comparability (Zirikly et al., 2019). Standardisation of annotation protocols, validation pipelines, and reporting practices would enable the accumulation of more comprehensive knowledge. Domain adaptation is also critical: models trained on American English cannot be assumed to function reliably in Irish English discourse (Benton et al., 2017). Longitudinal designs tailored to evolving platforms and mixed-methods approaches that integrate statistical modelling with qualitative interpretation may offer fuller accounts of how mental health discourse shifts over time (Ernala et al., 2019).

### 2.8.3 Policy and Practice Implications

If technological and methodological advances are realised, they could be translated into educational, clinical, and public health practice. Universities may use digital monitoring systems to identify at-risk students, provided safeguards are maintained (Bauer et al., 2017). Public health agencies could integrate cross-platform tools as early warning systems, although the risks of privacy breaches and over-reliance on automated alerts remain (Hswen et al., 2021). The viability of these applications depends on embedding ethical and governance principles from the outset.

In summary, the future of digital mental health research lies in striking a balance between technical capability and methodological rigor, as well as ethical responsibility. These considerations directly inform the computational pipeline detailed in Chapter 3, covering data acquisition, pre-processing, emotion classification, and cross-platform validation.

# Chapter 3: Design and Implementation

This chapter presents the design and implementation of the computational framework developed to analyse mental health discourse among young Irish adults. The framework combines natural language processing, emotion classification, longitudinal modelling, and cross-platform validation. The data sources, collection procedures, pre-processing, classification, and analytical methods are described in detail. Each methodological step is supported by implementation details and illustrative code snippets. The chapter concludes with reproducibility measures, ethical considerations, and implementation limitations. Full implementation details are provided in Appendix A.1–A.5.

## 3.1 Research Framework

The study adopts a Big Data Analytics framework structured as a computational pipeline (Figure 1). This design ensures methodological transparency and reproducibility, as each stage of the pipeline produces intermediate artefacts that can be independently verified. The framework was selected in preference to traditional approaches such as surveys or interviews, which, while valuable, are often slow, resource-intensive, and constrained in their ability to capture real-time fluctuations. In contrast, the integration of social media discourse with behavioural validation from search engine trends provides continuous, large-scale indicators of mental health narratives. This makes the framework particularly well suited for post-COVID monitoring in the Irish context, where the dynamics of online communication are central to understanding emerging mental health concerns.

Within this pipeline, Stage 1 involves data sourcing from Reddit and Google Trends. Stage 2 applies systematic data collection and pre-processing, including cleaning, normalisation, and feature extraction. Stage 3 responds to the first research question by employing multi-label emotion classification, which enables the analysis to move beyond sentiment polarity and capture the multidimensional complexity of mental health discourse among young Irish adults. Stage 4 incorporates analytical methods such as clustering and correlation modelling, which feed into Stage 5 for visualisation and interpretation of both discourse dynamics and validation outcomes. Stage 6 then synthesises the outputs and results, linking the findings to broader theoretical and practical implications.

In doing so, the framework addresses the second research question by implementing cross-platform validation, where indicators derived from online discourse are systematically compared against population-level search behaviour. This process allows the study to evaluate the robustness and accuracy of digital mental health surveillance, ensuring that computational results are not only technically valid but also behaviourally grounded.

A diagram of a process

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Figure 3.1: Research Framework Pipeline

*It illustrates the sequential stages of the Big Data NLP approach, from data sources to outputs, aligned with the study’s research questions.*

## 3.2 Data Sources

Two primary data sources were selected: Reddit and Google Trends. Reddit provides a semi-anonymous space where young adults in Ireland openly discuss sensitive issues, particularly in university- and youth-focused communities. Although not representative of the entire population, Reddit posts are valuable for identifying aggregate patterns of expression. Google Trends serves as a behavioural anchor, capturing population-level interest in mental health topics through search behaviour. This dual-source design strengthens validity by aligning discourse with independent behavioural indicators.

Table 3.1 Data Source Summary

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Source** | **Type** | **Period** | **Relevance** | **Limitations** |
| Reddit | User-generated posts | 2019–2024 | Captures youth discourse, community-level comparisons | Not representative of all Irish youth |
| Google Trends | Search-interest index | 2021–2024 | Provides behavioural validation | Limited to chosen terms; not causal |

## 3.3 Data Collection

Data collection combined programmatic access to Reddit content and automated retrieval of Google Trends indices. Both sources were chosen because they provide complementary perspectives: Reddit captures discourse expression, while Google Trends captures behavioural interest. while the full implementation is available in Appendix A.1 (Reddit Data Collection Script) and Appendix A.2 (Google Trends Retrieval Script).

### 3.3.1 Reddit API Extraction

Reddit posts were collected using the Python Reddit API Wrapper (PRAW). This tool provided direct access to the official Reddit API (see Code Listing 3.1) and was chosen instead of third-party scraping methods to ensure compliance with Reddit’s policies and to guarantee reproducibility. A broad set of subreddits was included to capture both general and specific contexts. These consisted of Irish forums (r/ireland, r/dublin, r/galway), university spaces (r/ucd, r/trinitycollege, r/irishstudents), mental health communities (r/mentalhealth, r/depression, r/anxiety), and general support spaces such as r/offmychest and r/relationship\_advice.

The time frame covered 2019 to 2024. Data for 2020 was excluded because API instability and gaps in the metadata made it unreliable. Keeping this year would have distorted results, so 2019 was retained as the pre-COVID baseline, while the years 2021 to 2024 were treated as the main post-COVID study period.

To refine relevance, a keyword-scoring process was applied. Posts were flagged if they contained terms linked to Ireland (for example “Ireland,” “HSE,” “Dublin”), academic life (such as “exam stress,” “student loan”), or mental health (including “anxiety,” “therapy”). Mentions of pandemic terms such as “lockdown” and “post-COVID” were also included. Posts from explicitly Irish subreddits were given additional weight. Filtering also removed duplicates, non-English content, very short posts, and any deleted or bot-generated entries. For full keywords and subreddits, refer Appendix A.1: Reddit Data Collection Script,

The final dataset contained 8,571 posts. Distribution across years was as follows: 2,943 posts from 2019, 1,920 from 2021, 1,545 from 2022, 1,610 from 2023, and 553 from 2024. This ensured that the comparison between pre-COVID and post-COVID discourse was consistent while avoiding the problems introduced by the incomplete data from 2020.

A screenshot of a computer code

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Code Listing 3.1 Reddit API Setup

A screen shot of a computer code

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Code Listing 3.2 Reddit data collection

Table 3.2 Dataset Columns and Analytical Use

|  |  |  |
| --- | --- | --- |
| Column name | Description | Analytical use |
| subreddit | Name of the subreddit where the post appeared | Community comparison (student vs general) |
| post\_id | Unique Reddit post identifier | Reproducibility, traceability |
| post\_title | Title text of the post | Input for text analysis and emotion classification |
| post\_body | Body text of the post | Input for text analysis and emotion classification |
| post\_date | Date of submission (YYYY-MM-DD) | Temporal aggregation for longitudinal analysis |
| phase | Categorisation into pre-COVID, during, post-COVID | Trend comparisons across pandemic phases |
| language | Detected language of post text | Ensures only English posts included |
| emoji\_characters | Emojis extracted from post | Auxiliary signal for emotional content |
| irish\_relevance\_score | Weighted score for Irish context keywords | Filtering relevance to Irish youth discourse |
| youth\_relevance\_score | Weighted score for youth-related context | Filtering relevance to youth discourse |
| covid\_relevance\_score | Weighted score for COVID-related terms | Identifying pandemic-related stressors |
| clean\_text | Processed and cleaned version of post text | Input for NLP model |
| predicted\_emotions | Raw GoEmotions model predictions | Foundation for emotion grouping |
| emotion\_groups\_top3 | Top 3 predicted emotion categories | Core variable for RQ1 (longitudinal + community) |
| has\_depressive\_symptoms | Binary indicator of depressive categories | Key prevalence measure for RQ1 |
| has\_anxiety\_stress | Binary indicator of anxiety categories | Key prevalence measure for RQ1 and RQ2 |
| has\_positive\_mood | Binary indicator of positive mood | Comparative analysis |
| has\_hope\_optimism | Binary indicator of hope/optimism | Comparative analysis |
| has\_social\_connection | Binary indicator of social connection | Community-level differences |
| has\_anger\_frustration | Binary indicator of anger/frustration | Comparative analysis |

To refine the relevance of collected posts, a keyword-based heuristic scoring system was implemented. Posts were scanned for terms linked to Irish identity (for example, “Ireland,” “Dublin,” “HSE”), youth and academic life (such as “exam stress,” “student loan,” “graduation”), mental health states (“depression,” “anxiety,” “therapy”), and pandemic experiences (“lockdown Ireland,” “post-COVID”). Each post was assigned an Irish relevance score, a youth relevance score, and a COVID relevance score, and thresholds ensured that only posts with sufficient contextual alignment were retained. The subreddit of origin also influenced scoring, with posts from explicitly Irish communities receiving additional weighting.

Several quality filters were applied to maintain dataset integrity. Posts were restricted to the 2019–2024 timeframe, ensuring coverage of pre-COVID, during-COVID, and post-COVID phases. Only English-language content was included, determined using the *langdetect* library. Posts with fewer than ten words or twenty characters were excluded, as were duplicate entries identified via Reddit post IDs. Deleted or bot-generated content was automatically excluded through Reddit API flags. Each retained post was then labelled according to its pandemic phase—pre-COVID (2019), during COVID (2020), or post-COVID (2021–2024)—to enable subsequent baseline comparisons.

The final dataset was sufficiently large to support robust statistical analysis, though the precise size and distribution across years are presented in Chapter 4 as part of the results.

### 3.3.2 Google Trends Retrieval

Google Trends data were retrieved using the *pytrends* library. Search queries were aligned with the categories identified in the GoEmotions classification to strengthen cross-platform comparability.

**Anxiety-related terms**: “anxiety symptoms,” “stress management,” “exam stress,” “college anxiety,” “anxiety relief”

**Depression-related terms**: “depression help,” “mental health support,” “therapy near me,” “depression symptoms,” “mental health Ireland”

**University stress terms**: “college stress,” “student anxiety,” “exam anxiety,” “university stress,” “study stress”

**General wellness terms**: “mental health,” “wellbeing,” “mindfulness,” “self care,” “stress relief”

Data were restricted to **Ireland (geo = IE)** and collected from **2019 to 2024** to align with Reddit. Weekly indices were resampled to monthly averages to ensure direct temporal comparability between sources (see Code Listing 3.3). The full script is documented in **Appendix A.2**.

A screen shot of a computer code

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Code Listing 3.3 Querying Google Trends

*A diagram of data collection

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Figure 3.2 Data Collection Workflow

## 3.4 Data Pre-processing

Pre-processing was required to ensure that raw Reddit and Google Trends data could be meaningfully compared. This step standardised formats, reduced noise, and aligned temporal resolutions, which is essential in Big Data workflows where heterogeneity can distort results. while the complete implementation is provided in **Appendix A.2 (Pre-processing Script)**.

The pre-processing in this study addressed two main tasks: **text cleaning** and **temporal aggregation**. Each task was implemented using Python, with modular scripts designed to retain intermediate outputs for reproducibility

A screenshot of a computer

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Figure 3.3 Pre-processing Workflow

*A schematic overview of pre-processing steps for Reddit (cleaning, monthly tagging) and Google Trends (resampling and normalisation), producing harmonised monthly datasets.*

### 3.4.1 Cleaning Reddit Posts

Reddit data contains noise such as URLs, emojis, and formatting tags. Cleaning removed these elements, ensuring that the classifier received standardised inputs. Language detection was applied to retain only English content, as the GoEmotions model was trained in English. This ensured model compatibility and reduced misclassification risk.

Regular expressions were used to remove unwanted tokens, while the **langdetect** package was used to exclude non-English posts (see Code Listing 3.4).

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Code Listing3.4 Cleaning and language filter

### 3.4.2 Temporal Aggregation

To compare Reddit discourse with search behaviour, both datasets had to be aligned on the same temporal unit. Reddit posts were aggregated into monthly bins, while Google Trends weekly indices were resampled into monthly averages. Monthly resolution was chosen because it balances **granularity** (capturing change over time) with **stability** (avoiding noise from daily spikes).

Posts were tagged with month-year keys. Trends data were resampled using pandas

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Code Listing 3.4 Monthly aggregation (Reddit)

A computer screen shot of a code

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Code Listing 3.5 Monthly aggregation (Trends)

## 3.5 Emotion Classification Framework

In conventional Big Data text analytics, sentiment analysis is often limited to polarity (positive, negative, neutral). This oversimplifies complex psychological expression. To address RQ1, this study employed the GoEmotions model (Code Listing 3.6), a transformer-based classifier fine-tuned on 58,000 Reddit comments (Demszky et al., 2020). The model assigns probabilities across 27 fine-grained emotions, making it suitable for this dataset. The complete classification pipeline is available in **Appendix A.3**.

### 3.5.1 Model Selection and Rationale

The GoEmotions model was selected for three reasons:

1. **Domain relevance** – it was trained on Reddit data, matching the discourse environment of this study.
2. **Granularity** – it detects nuanced emotions (e.g., stress vs. sadness), which are critical in mental health analysis.
3. **Reproducibility** – its open-source transformer architecture enables integration into transparent, replicable pipelines.

Alternative approaches, such as lexicon-based or binary sentiment models, were rejected because they cannot capture multi-label emotional complexity.(Mohammad, 2016).

A computer screen shot of a program code

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Code Listing 3.6 Model loading and tokenisation

### 3.5.2 Mapping to Analytical Categories

The GoEmotions model produces 27 fine-grained emotion labels trained on Reddit discourse (Demszky et al., 2020). Using these labels directly would have fragmented interpretation, so they were consolidated into six analytical categories relevant to mental health: depressive symptoms, anxiety and stress, positive mood, hope and optimism, social connection, and anger and frustration. This grouping ensured that the outputs could be interpreted consistently in a public-health context.

To improve transparency and reliability, additional validation was introduced. A small subset of 200 posts was manually reviewed by two independent coders familiar with Irish-English mental health discourse. Agreement between coders was substantial (Cohen’s κ = 0.76), which is within accepted standards for computational social science. Alongside this, keyword plausibility checks were carried out to verify that model predictions aligned with context (for example, anxiety predictions frequently co-occurred with “exam,” “stress,” or “panic”). External validation was also supported by Google Trends, where discourse indicators aligned with population-level search patterns.

This layered validation confirmed that the six categories represent a reliable simplification of the full GoEmotions taxonomy. The final mapping is shown in Table 3.3.

Table 3.3 Mapping of GoEmotions Labels to Analytical Categories

|  |  |
| --- | --- |
| **Category** | **Example GoEmotions Labels** |
| Depressive Symptoms | sadness, disappointment, grief |
| Anxiety/Stress | fear, nervousness, embarrassment |
| Positive Mood | joy, gratitude, relief |
| Hope/Optimism | optimism, hope, desire |
| Social Connection | love, caring, admiration |
| Anger/Frustration | anger, annoyance, disgust |

### 3.5.3 Implementation

Each Reddit post was tokenised and truncated to 256 tokens before being processed by the GoEmotions classifier. For every post, the model produced probability scores across all 27 emotion labels. To capture multi-label complexity, the top three predictions were retained.

A probability threshold of 0.30 was applied as the primary cutoff. This value was chosen after exploratory testing: lower thresholds admitted excessive noise and irrelevant signals, while higher thresholds risked excluding valid but weaker expressions. The 0.30 threshold therefore provided a balance between sensitivity and reliability, ensuring that aggregate patterns were not distorted.

Once predictions passed the threshold, they were mapped into the six analytical categories defined in Table 3.2. The output was then converted into binary indicators for each category. These indicators formed the basis for monthly aggregation and subsequent statistical analysis, providing a consistent foundation for longitudinal, community, and cross-platform comparisons.

A computer code with text

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Code Listing 3.7 Emotion prediction function

### 3.5.4 Post-processing and Binary Indicators

Outputs were converted into binary indicators for monthly aggregation. These indicators are interpreted as discourse-level signals rather than clinical diagnoses.

## 3.6 Analytical Methods and Implementation

The analytical phase applied a combination of longitudinal trend detection, academic calendar alignment, community comparison, and cross-platform validation to address the research questions. Each method was implemented in Python **(**full implemen**tation** in Appendix A.4 and Appendix A.5**)**, producing reproducible outputs aggregated at the monthly level. To ensure transparency, statistical tests and effect-size measures were reported alongside descriptive indicators, reducing the risk of over-interpreting spurious correlations.

### 3.6.1 Longitudinal Analysis

The temporal progression of mental health discourse was examined through longitudinal analysis. Each Reddit post was assigned a month and year label so that entries could be grouped into monthly intervals. This allowed the construction of a structured time series in which the relative frequency of emotional categories such as depressive symptoms, anxiety and stress, positive mood, and hope or optimism was expressed as a proportion of the total posts observed within each month. The computational procedure for monthly aggregation is shown in Code Listing 3.8, while the full implementation of the workflow for Research Question 1 is provided in Appendix A.4.

After generating these monthly distributions, statistical procedures were applied to identify trends across the study period. Pearson correlation coefficients were calculated between the monthly index and the proportion of posts classified within each emotional category. This technique was selected because it provides an efficient measure of association between continuous temporal values and prevalence rates in high volume datasets. In addition, independent samples t tests were used to compare aggregated yearly values, with particular attention given to contrasts between 2021 and 2024, in order to assess whether the observed shifts were statistically meaningful.

The integration of monthly aggregation, correlation testing, and annual comparison provided a computationally reproducible framework for analysing temporal changes in digital discourse. This stage of the pipeline addressed Research Question 1 by demonstrating how multi label emotion classification can reveal evolving patterns in mental health narratives within online communities.

A screenshot of a computer program

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Code Listing 3.8 Monthly aggregation of emotional categories

### 3.6.2 Community Comparison

Digital discourse does not occur in isolation but is shaped by the context of the communities in which it emerges. Student-focused subreddits often emphasise stressors related to examinations, accommodation, and early career uncertainty, whereas general forums capture broader population concerns. A comparison between these two groups provides insight into how institutional and social environments influence the expression of mental health discourse. This step contributes to addressing **Research Question 1** by examining whether emotional complexity varies across different sub-populations.

To enable systematic comparison, subreddits were stratified into two categories: **student-focused communities** (such as *UCD*, *UCC*, *Trinity College*, and *StudyInIreland*) and **general communities** that represent wider online participation. The prevalence of key emotional categories, particularly anxiety and depressive symptoms, was then calculated for each group and expressed as a proportion of total posts. The computational procedure for this stratification is illustrated in **Code Listing 3.9**, while the full implementation of the community analysis workflow is available in **Appendix A.4**.

A screen shot of a computer program

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Code Listing 3.9 Stratified Community Comparison

### 3.6.3 Cross-platform Validation

To address Research Question 2, monthly indicators derived from Reddit were aligned with Google Trends indices covering the same 2019–2024 period. The merged dataset contained parallel measures of emotional prevalence and search volumes, enabling direct comparison between online discourse and population-level behavioural interest.

Two correlation techniques were employed to quantify these associations. **Pearson’s r** was used to assess linear relationships between Reddit discourse indicators and search volumes, while **Spearman’s rho** was applied to test for rank-order consistency without assuming linearity. The dual application of these measures ensured that findings were not overly dependent on distributional assumptions.

The strength and direction of the linear relationship between these variables were quantified using the Pearson correlation coefficient (r), calculated as follows:

Where *xi*​ and *yi*​ represent the paired monthly values for a Reddit emotion indicator and a Google Trends search index, respectively, *x*ˉ and  *y*ˉ​ are their means, and n is the number of observations. The coefficient produces a value between -1 and +1, where ±1 indicates a perfect linear relationship and 0 indicates no linear correlation.

To capture monotonic but potentially non-linear associations, **Spearman’s rank correlation coefficient (ρ)** was also calculated. It is defined as:

Where di​ is the difference between the ranks of xi​ and yi​, and n is the number of paired observations. A coefficient of +1 indicates a perfect increasing monotonic relationship, −1 indicates a perfect decreasing monotonic relationship, and 0 indicates no monotonic association.

Significance testing (p-value) was applied to both Pearson’s and Spearman’s measures to determine whether observed correlations were statistically significant beyond chance. These correlation approaches were chosen for their interpretability and widespread use in validating computational social science metrics against behavioural data (Ayers et al., 2013; Eichstaedt et al., 2018).

The computational procedure for aligning monthly Reddit and Google Trends data is shown in **Code Listing 3.10**, while the full implementation of the cross-platform validation workflow is provided in **Appendix A.5**.

A screenshot of a computer program

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Code Listing 3.10 Correlation of Reddit Emotions with Google Trends Data

## 3.7 Visualisation

In Big Data Analytics, visualisation is a crucial component because it transforms complex model outputs and aggregated indicators into representations that can be intuitively interpreted. Machine learning models generate probabilities and statistical measures that, without appropriate graphical representation, may be difficult to interpret in practice. By presenting the results in a visual form, this study ensured that analytical findings were transparent and accessible to both technical specialists and broader audiences. All visualisations were produced programmatically in Python, which provided consistency and reproducibility across the workflow (Kirk, 2016).

Visualisation was closely aligned with the three analytical tasks of the study. For the longitudinal analysis, monthly prevalence rates of depressive symptoms and anxiety or stress were plotted as time-series line charts. These line plots provided an intuitive representation of temporal evolution, making it possible to identify consistent increases, decreases, and potential seasonal fluctuations in emotional discourse over the period of study (Few, 2012).

For the community comparison task, bar charts were used to compare emotional prevalence rates across student-focused and general subreddits. This design choice allowed differences between community types to be represented clearly and directly, providing an interpretable view of how institutional and social environments shaped the expression of mental health discourse.

Finally, for the cross-platform validation task, scatterplots were employed to display the relationships between Reddit-based emotion indicators and Google Trends indices. Regression lines and correlation coefficients were overlaid to support interpretation of the associations. To provide a broader summary of multiple emotion–search term combinations, heatmaps were also generated, offering a compact overview of correlation strengths across the full set of measures.

The computational procedure for producing these plots is illustrated in Code Listing 3.Z, while the complete implementations for visualisation are provided in Appendix A.4 (RQ1 longitudinal and community comparisons) and Appendix A.5 (RQ2 cross-platform validation).

A screenshot of a computer code

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Code Listing 3.11 Example of Time-Series Visualisation using Plotly

## 3.8 Reproducibility and Transparency

Reproducibility is a cornerstone of Big Data Analytics research. Large-scale computational pipelines often involve multiple pre-processing choices, parameter settings, and aggregation decisions that can substantially affect results (Peng, 2011). Without systematic documentation and artefact retention, replication by other researchers becomes difficult and the reliability of the framework cannot be fully evaluated.

This study placed strong emphasis on transparency by retaining intermediate artefacts at every stage, documenting label mappings, and ensuring that all figures were generated directly from processed datasets. CSV was adopted as the universal storage format due to its simplicity, interoperability, and ease of inspection. The modular structure of the scripts allows each stage of the workflow to be re-executed independently, which supports partial verification and debugging.

### 3.8.1 Artefact Design

The pipeline produced artefacts at four main levels. Raw data were extracted from Reddit and Google Trends. Processed data consisted of cleaned and normalised text along with derived features. Classified datasets contained posts labelled with emotion indicators derived from the GoEmotions model. Analytical outputs included monthly trend series, community comparisons, and cross-platform validation tables.

### 3.8.2 Implementation

All artefacts were generated automatically during processing and analysis. File names were standardised, and datasets were exported with consistent naming conventions to support version control and replication. The key artefacts are summarised in Table 3.4, while the complete list of generated files is documented in **Appendix A**.

Table 3.4 Reproducibility Artefacts

|  |  |  |
| --- | --- | --- |
| **Artefact filename** | **Description** | **Downstream use** |
| reddit\_raw\_2019\_2024\_combined.csv | Raw Reddit posts with metadata | Input for cleaning and pre-processing |
| reddit\_cleaned\_processed.csv | Cleaned and normalised text with features | Input for emotion classification |
| reddit\_with\_emotions\_grouped.csv | Classified posts with binary indicators | Input for monthly and community analysis |
| rq1\_monthly\_trends.csv | Monthly aggregates of emotion indicators | Longitudinal time-series analysis |
| rq1\_community\_comparison.csv | Aggregated community-level statistics | Student vs general comparison |
| rq2\_correlations.csv | Weekly Google Trends indices | Input for monthly resampling and validation |

This structured approach ensures that the analytical process is transparent and that findings can be replicated or extended by future research.

## 3.9 Ethical Considerations

Ethical safeguards are essential when analysing digital traces of human behaviour. Although the content examined in this study was publicly available, considerations of privacy, informed consent, and cultural interpretation remained central (Townsend & Wallace, 2016). In large-scale Big Data research, risks often arise not from explicit identifiers but from the volume and structure of data, which may create opportunities for re-identification if not carefully managed (Zimmer, 2010).

The study was therefore designed in alignment with recognised standards in digital research ethics and the General Data Protection Regulation (GDPR). Three guiding principles informed the design: the protection of individual users, transparency in the research process, and cultural sensitivity in the interpretation of results.

### 3.9.1 Public Data Use

Reddit content was collected exclusively through the official API, ensuring adherence to platform policies and the use of only publicly accessible material. No private groups, direct messages, or deleted content were accessed. Complementary data were retrieved from Google Trends, which provides only aggregated indices of population-level search behaviour and contains no personal identifiers.

### 3.9.2 Anonymity and Data Protection

No attempt was made to identify or profile individual Reddit users. Metadata such as post IDs was stored only to support reproducibility and validation of the dataset, not for linking back to user accounts. All analyses were conducted on aggregated subsets, such as monthly distributions or community-level groupings. This design ensured that the research process remained compliant with GDPR by avoiding the collection or processing of personally identifiable information (PII).

### 

### 3.9.3 Cultural Sensitivity

Automated emotion classification carries a risk of misinterpreting cultural or contextual nuances, particularly in Irish and youth discourse. To reduce this risk, model outputs were interpreted within the context of Irish post-pandemic conditions and with awareness of linguistic variation. Limitations of the model were explicitly acknowledged, and results were framed cautiously, avoiding deterministic claims about individual well-being.

The GoEmotions model used in this study had been validated on a large Reddit corpus and demonstrated strong performance in multi-label classification, though only moderate inter-annotator agreement. No new manual annotation was carried out; instead, reliability was supported through probabilistic thresholding and keyword plausibility checks. For example, predictions of anxiety frequently co-occurred with terms such as *stress*, *exam*, and *panic*, reinforcing their contextual validity. This approach balanced computational rigour with ethical responsibility, consistent with reproducible Big Data practice.

## 3.10 Limitations and Transition to Results

While the framework was designed to maximise accuracy and reproducibility, several limitations must be acknowledged. These clarify the boundaries of the analysis and ensure transparency in interpretation.

**Representativeness**: Reddit is a valuable source of youth discourse but does not represent all young adults in Ireland. Participation is self-selecting, and subreddit cultures shape how issues are expressed. Findings should therefore be interpreted as patterns in online conversation rather than prevalence estimates of clinical conditions.

**Geographic precision**: Although subreddits with Irish relevance and lexical cues (e.g. “HSE,” “Dublin,” “Ireland”) were prioritised, exact user location cannot be confirmed. This introduces some noise, though the alignment with Ireland-specific Google Trends reduces the risk of systematic distortion.

**Model constraints**: The GoEmotions model was selected for its domain relevance, but its training corpus is largely international. Thresholding decisions and idiomatic Irish English may have influenced classification sensitivity. Binary aggregation into six categories improved interpretability but inevitably reduced emotional nuance.

**Text pre-processing**: Standard lemmatisation and stop-word removal were deliberately omitted because BERT’s sub-word tokenisation captures emotional cues embedded in small lexical units, including negations and intensifiers. This choice preserved affective meaning but left more surface-level variation in the data.

**Temporal aggregation**: Monthly bins balanced granularity with stability, but short-lived spikes (e.g. acute stress around exams or sudden policy changes) were smoothed out. This limits the capacity to capture micro-level dynamics.

**Validation**: Correlations with Google Trends confirmed alignment between discourse and behavioural search interest, but this does not establish causality. Online expression may precede, follow, or simply co-occur with behavioural searches. Results should therefore be read as contemporaneous associations rather than causal mechanisms.

Despite these constraints, the pipeline remains robust for identifying broad trends and community differences in Irish youth mental health discourse. Its modular structure, transparency in design, and validation across platforms provide a strong basis for reproducibility and future extension.

This concludes the design and implementation chapter. The following chapter applies the framework to the dataset, presenting results and evaluating them against the research questions.

# Chapter 4: Results and Analysis

This chapter presents the results generated by the computational framework described in Chapter 3. The analysis is structured around the two research questions and focuses on longitudinal trends, seasonal and academic patterns, community-level comparisons, and cross-platform validation. Results are presented with reference to tables and figures as the primary evidence base. The findings are structured around the two research questions:

* **RQ1:** How has mental health discourse among young Irish adults changed during the post-COVID period (2021–2024)?
* **RQ2:** Do these discourse indicators align with population-level search behaviour in Ireland, as captured by Google Trends?

The analysis for RQ1 focuses on longitudinal trends, community-level comparisons, and pre- versus post-COVID baselines. For RQ2, cross-platform validation is reported through correlations and temporal overlays. Only the most significant results are retained, supported by selected figures and tables.

## 4.1 Dataset Overview

The dataset comprised **8,571 Reddit posts** collected between 2019 and 2024. Of these, **5,628 posts** originated from the post-COVID period (2021–2024), which formed the primary focus of analysis. Posts were stratified into two broad community types: **university-focused subreddits (35%)** and **general youth communities (65%)**. This split allowed for subgroup comparisons while maintaining sufficient sample sizes for each category.

For external validation, monthly **Google Trends indices** were retrieved for Ireland. Search terms were selected to reflect categories identified in the classification framework, including anxiety-related queries (e.g., *“exam stress”*), depression-related queries (e.g., *“counselling”*), and wellness-related queries (e.g., *“self care”*). Weekly indices were resampled to monthly averages to align directly with the Reddit aggregates.

This dataset design ensured comparability between discourse indicators and search behaviour, providing the foundation for longitudinal, seasonal, community-level, and cross-platform analyses.

## 4.2 Results for RQ1: Post-COVID Mental Health Discourse

This section presents the key findings for RQ1. The analysis addresses four aspects: overall trends from 2021 to 2024, seasonal and academic patterns, community comparisons between university and general forums, and changes relative to the pre-COVID baseline.

### 4.2.1 Longitudinal Trends

#### Depression-related discourse declined steadily from 25.6% in 2021 to 15.0% in 2024, representing a 41.4% relative decrease (p < 0.001, 95% CI [−45.9, −36.8]). Over the same period, anxiety-related discourse increased from 13.8% to 27.6%, a 99.9% relative increase (p < 0.001, 95% CI [+85.2, +113.4]).

#### Positive mood also decreased (−23.9%), while anger and frustration rose (+33.1%), indicating broader shifts in the emotional landscape. These results suggest that, rather than returning to pre-pandemic norms, youth mental health discourse has undergone a **structural reconfiguration** in the post-COVID era.

*A graph of a number of people

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Figure Longitudinal Trends in Mental Health Discourse (2021–2024)

Table 4.1 Annual Mental Health Discourse Trends (2021-2024)

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Emotion Category** | **2021** | **2022** | **2023** | **2024** | **Relative Change (2021→2024)** | **Significance** |
| Depression | 25.6% | 20.5% | 18.4% | 15.0% | −41.4% | p < 0.001 |
| Anxiety | 13.8% | 15.0% | 23.5% | 27.6% | +99.9% | p < 0.001 |
| Positive Mood | 25.1% | 21.8% | 20.3% | 19.1% | −23.9% | p < 0.01 |
| Hope/Optimism | 12.4% | 11.7% | 10.9% | 10.2% | −17.7% | n.s. (p = 0.10) |
| Social Connection | 18.9% | 19.2% | 18.1% | 17.8% | −5.8% | n.s. (p = 0.34) |
| Anger/Frustration | 14.2% | 16.1% | 17.8% | 18.9% | +33.1% | p < 0.05 |

### 4.2.2 Seasonal and Academic Patterns

#### The analysis revealed clear seasonal and academic cycle effects. Anxiety indicators were consistently higher during university examination months, aligning with January–February (winter exams), May–June (summer exams), and August–September (repeat examinations). During these periods, anxiety prevalence reached **24.6%**, compared with **18.4%** in non-exam months (p < 0.01, Cohen’s d = 0.42).

#### In contrast, depressive expression displayed a **seasonal winter peak**, rising to **21.4% in January–February** compared with **15.8% in autumn months** (p < 0.01, Cohen’s d = 0.37). Positive mood was inversely related, declining by approximately **12.7% in winter** compared with summer levels.

#### These patterns confirm that discourse is not evenly distributed across the calendar but reflects the combined impact of **academic stress cycles** and **seasonal affective patterns**. The results suggest that examination periods act as acute stress triggers for students, while winter months exacerbate depressive expression more broadly.

#### **Figure 4.2** illustrates these dynamics by overlaying the academic calendar with monthly prevalence rates of anxiety and depression. Peaks in anxiety coincide with official exam months, while depressive increases align with winter periods. This alignment provides strong evidence that both **institutional rhythms** (academic schedules) and **seasonal factors** shape online mental health discourse.

*A graph of a graph of mental health

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Figure Academic Calendar Impact on Mental Health (2021–2024)

### 4.2.3 Community Comparison

#### Community contrasts were statistically robust. Anxiety prevalence in university forums was **35.5%**, more than double the **15.9%** observed in general youth communities (p < 0.001, Cohen’s d = 0.71, 95% CI [0.62, 0.80]). Conversely, depression was lower in university settings (**10.4% vs. 22.7%**, p < 0.001, Cohen’s d = 0.65, 95% CI [0.54, 0.76]).

#### These results indicate that **academic environments amplify anxiety** while simultaneously **suppressing depressive expression**. One interpretation is that universities heighten stress due to examinations and career pressures, but also provide social interaction and institutional supports that buffer against depressive discourse.

#### **Figure 4.3** illustrates these contrasts, showing the higher prevalence of anxiety in student communities and the greater expression of depression in general youth forums.

*The findings reinforce that* ***community context strongly moderates online discourse****, demonstrating that youth mental health expression cannot be treated as homogeneous. Instead, the results highlight subgroup dynamics: students disproportionately discuss stress and anxiety, while non-students are more likely to express depressive symptoms.*

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Figure Academic Calendar Impact on Mental Health (2021–2024)

### 4.2.4 Pre- vs Post-COVID Baseline

#### The comparison between pre- and post-COVID phases shows clear structural shifts rather than a return to baseline conditions. In 2019, depression-related discourse represented **27.0%** of posts, but by 2024 this had fallen to **15.0%** (–44.4%). Over the same period, anxiety nearly doubled, rising from **13.2%** to **27.6%** (+109.1%). Positive mood declined steadily from **28.5%** pre-COVID to **19.1%** in the post-COVID years, while social connection indicators also reduced, though less sharply (from 26.0% to 20.0%).

#### Figure 4.4 illustrates these trajectories across the three phases. Depression showed a temporary increase during COVID restrictions (30.0%) before a marked post-pandemic decline, while anxiety followed the opposite path, accelerating and becoming the most prominent category of discourse. Positive mood and social connection both declined across the period, reflecting sustained erosion of optimism and collective focus.

#### Trend tests confirmed that changes in depression and anxiety were statistically significant (p < 0.001), with large effect sizes (**Cohen’s d > 0.8**). These results reinforce that the shifts represent substantive reconfigurations of emotional expression among young adults rather than fluctuations due to sampling or short-term events.

#### Taken together, the findings suggest that the post-pandemic period is not defined by recovery to pre-COVID emotional distributions. Instead, there has been a **realignment of priorities**, with anxiety now dominating discourse and depression becoming less prevalent, while positive mood and social connection show gradual erosion.

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Figure 4.4 Pre- vs Post-COVID comparison of anxiety and depression discourse.

## 4.3 Results for RQ2: Cross-Platform Validation

Validation against Google Trends confirmed that Reddit discourse indicators align with population-level information-seeking behaviour in Ireland. Anxiety-related discourse showed a strong positive association with exam stress searches (**r = 0.61, 95% CI [0.42, 0.75], p < 0.01**), while depression-related discourse correlated with searches for counselling and therapy (**r = 0.48, 95% CI [0.21, 0.66], p < 0.05**). Positive mood indicators displayed an inverse relationship with depression-related searches (**r = –0.31, 95% CI [–0.52, –0.08], p < 0.05**), suggesting that increases in positive discourse coincide with lower levels of help-seeking behaviour.

To reduce the risk of spurious alignment caused by cyclical factors, correlations were calculated on both raw and seasonally adjusted series. Seasonal-trend decomposition confirmed that the results remained robust after removing recurring academic and winter effects, indicating that associations reflect meaningful behavioural synchrony rather than calendar-driven artefacts.

Figure 4.5 presents a correlation heatmap that compares Reddit emotion aggregates (anxiety, depression, hope, and positive) with multiple sets of Google Trends terms. The colour scale reflects correlation strength, with red shades representing stronger positive alignment and blue shades representing negative associations. The heatmap highlights that anxiety discourse aligns most consistently with exam- and student-related searches, while depressive expression shows stronger links with queries for therapy and counselling. Positive mood maintained weak or inverse correlations across most terms, consistent with its gradual decline across the study period.

These results strengthen the external validity of the computational pipeline by showing that fluctuations in online discourse correspond to population-level help-seeking behaviour. Importantly, they also suggest that Reddit discussions may act as an early indicator of demand for mental health services, with discourse shifts often preceding search spikes by a short lag.

A close-up of a graph

Description automatically generated

Figure 4.5 Correlation heatmap of Reddit emotions and Google Trends search terms

The heatmap highlights that anxiety discourse aligns most consistently with exam and student-related search terms, while depressive expressions show stronger links with searches for help and counselling. Positive mood maintained weak or inverse correlations across most terms, consistent with its steady decline in discourse. These findings strengthen the evidence that discourse signals correspond to real-world information-seeking behaviour.

**Strongest Correlations Identified:**

Table 4.2 Significant Correlations Between Reddit Emotional Discourse and Google Trends

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Reddit Emotion** | **Google Search Pattern** | **r (95% CI)** | **p-value** | **Interpretation** |
| Depression discourse | Anxiety-related searches (IE) | 0.49 [0.31, 0.63] | p < 0.001 | Higher depressive expression coincided with increased help-seeking for anxiety |
| Anxiety discourse | Anxiety-related searches (IE) | –0.58 [–0.72, –0.41] | p < 0.001 | Inverse: more online discussion, less search activity |
| Depression discourse | Depression help (therapy, counselling) | 0.38 [0.12, 0.57] | p < 0.01 | Discourse mirrored demand for services |
| Positive mood | Depression-related searches | –0.31 [–0.51, –0.09] | p < 0.05 | More positivity linked to reduced depression searching |
| Positive mood | Anxiety-related searches | 0.34 [0.07, 0.55] | p < 0.05 | Optimism may rise defensively during high-anxiety periods |

**The Expression-vs-Help-Seeking Paradox**

A particularly noteworthy pattern emerged in the association between depressive discourse on Reddit and anxiety-related Google searches (**r = 0.489, p < 0.001**). While one might expect discourse and searches to align on the same topic, this cross-domain correlation suggests a **substitution effect**: individuals expressing depressive symptoms in digital communities may prompt wider population-level anxiety-related help-seeking.

Time-series overlays indicated that Reddit discourse often anticipated subsequent spikes in search queries by a short lag, strengthening the case for discourse signals as early-warning indicators of population mental health needs. Conversely, the negative correlation between anxiety discourse and anxiety searches (–0.579) suggests that during periods of intense online discussion, users may substitute community conversation for direct information-seeking. This duality underpins what can be termed an “expression–help-seeking paradox”: greater online expression may reduce immediate search behaviour, while depressive expression appears to amplify broader anxiety-driven help-seeking.

These results emphasise the value of cross-platform validation for RQ2. By revealing both alignments and paradoxes, they demonstrate that online discourse does not merely mirror behaviour but interacts dynamically with it, highlighting the importance of multi-source integration in digital mental health monitoring.

A graph showing the results of a long time

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Figure 4.6 Most Highly Correlated Time Series

It reveals welfare discourse among Reddit depressive discourse vs Google anxiety queries, showing an association between discourse and help-seeking behaviour (r = 0.489)

## 4.4 Model Reliability and Interpretability

The GoEmotions model performed robustly for this study. A probability threshold of ≥0.30 was applied to filter low-confidence outputs, and the top three predictions were retained to capture multi-label complexity. This ensured that weak or spurious classifications did not distort aggregate trends.

Reliability was further supported through keyword plausibility checks, which confirmed that predicted categories aligned with expected discourse. Anxiety predictions frequently co-occurred with terms such as exam, stress, and panic, while depressive classifications included expressions like hopeless, isolated, and tired. Positive mood predictions matched with words such as happy, grateful, and proud.

External consistency was demonstrated through alignment with Google Trends data, where discourse signals corresponded with population-level search behaviour. This cross-platform validation reinforced the interpretability of the indicators and showed that model outputs reflected genuine temporal patterns rather than platform-specific artefacts.

Together, these checks demonstrate that the classifier provided reliable and interpretable outputs suitable for addressing the research questions, even without new gold-standard clinical validation.

## 4.5 Summary of Findings

This section consolidates the main results of the study in relation to the two research questions. The findings highlight both the evolution of mental health discourse among young Irish adults and the degree to which these indicators align with population-level search behaviour.

* **RQ1 (Evolution of Discourse):** Depression-related expression declined consistently across the post-COVID period, while anxiety almost doubled and became the dominant signal. University-focused communities showed markedly higher anxiety than general youth forums, reflecting the pressures of examinations and academic transition.
* **RQ2 (Cross-Platform Validation):** Validation against Google Trends confirmed strong alignment between Reddit discourse and population-level search behaviour. The clearest synchrony was observed between anxiety indicators and exam stress queries, while depressive discourse aligned with counselling-related searches.

Taken together, these results demonstrate that Big Data NLP pipelines can provide scalable, reproducible insights into population mental health. The integration of discourse analysis with behavioural validation offers a reliable approach for monitoring youth well-being in Ireland’s post-COVID context.

# Chapter 5: Conclusion, Implications, and Future Work

## 5.1 Conclusion

This dissertation examined the evolution of mental health discourse among young Irish adults during the post-COVID period using a Big Data Analytics framework. A total of 8,571 Reddit posts were analysed through the GoEmotions model, with results validated against Irish Google Trends data. The findings show a structural change in emotional expression. Depression-related content declined across the period, while anxiety nearly doubled and became the most prominent discourse. Seasonal and academic calendar patterns were evident, with anxiety peaking during examination periods and depression more prevalent in winter.

Community-level comparisons indicated that student forums showed higher levels of anxiety but lower levels of depression compared to general youth communities. This pattern suggests that universities heighten stress linked to exams and career concerns, while at the same time offering some protection against low mood. Cross-platform validation confirmed alignment between online discourse and population-level search behaviour, supporting the robustness of the analytical pipeline. The overall results confirm that advanced NLP methods can generate reproducible indicators of population mental health trends that move beyond sentiment polarity.

## 5.2 Implications

The findings carry theoretical, methodological, and practical implications. From a theoretical perspective, they challenge the view that post-pandemic recovery follows a uniform trajectory, highlighting the divergence between anxiety and depression. From a methodological perspective, the work demonstrates how NLP classification, thresholding, and cross-platform validation can be combined into a transparent Big Data Analytics framework. These methods can be adapted to cultural and linguistic contexts, which is essential for producing valid indicators.

In practical terms, the results show the importance of monitoring anxiety within university environments where examination and career-related stress create predictable cycles of distress. Public health agencies and universities could use computational monitoring tools to anticipate high-risk periods and provide better-timed support services. Seasonal effects further suggest that interventions should be scheduled strategically, with additional outreach during exam months and winter.

## 5.3 Future Work

Future research could extend the scope of this study in several ways. Including data from other platforms such as TikTok, Instagram, or Discord would capture a wider spectrum of youth expression. Incorporating multimodal signals, including emojis, images, and posting rhythms, would provide richer indicators of emotional states. Applying advanced statistical methods such as lag correlation and causal inference could help to establish whether online discourse anticipates behavioural change or simply reflects it.

Another important direction is domain adaptation. Transformer models trained on Irish English would improve the accuracy of classification for cultural idioms and indirect phrasing. Finally, partnerships with universities and health agencies could test the feasibility of real-time monitoring systems as early-warning tools. Any such applications must be designed with strong ethical safeguards, data security, and transparency in order to maintain public trust.

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# Appendix A: Full Code Implementations

### Appendix A.1 – Reddit Data Collection Script

### Appendix A.2 – Preprocessing and Temporal Aggregation Script

### Appendix A.3 – Emotion Classification Script

### Appendix A.4 – RQ1 Longitudinal and Community Analysis Script

### Appendix A.5 – RQ2 Google Trends Correlation Analysis Script