The Journal of Computational Science and Engineering (TJCSE)
ISSN 2583-9055 (Media Online)
Vol 3, No 5, May 2025
PP 16−15

Digital Technology and Social Isolation: A Machine Learning Study of Wellbeing Patterns

Sanjana Panda[1]
[1]Thakur Institute of Management Studies Career Development and Research
Mumbai, India
Corresponding Author *: sanjanaspanda@gmail.com

Abstract

The intersection of loneliness, technology usage, and community dynamics plays a critical role in shaping individual wellbeing in contemporary society. This study explores how these variables interact, using a diverse and generalized dataset collected through a comprehensive questionnaire. The analysis incorporates both quantitative data and qualitative insights derived from open-ended responses, leveraging sentiment analysis and natural language processing (NLP). By employing machine learning models, the study identifies key factors influencing wellbeing, uncovers patterns in loneliness and technology use, and highlights the role of community engagement in mitigating adverse effects. The findings offer actionable insights for designing technology-driven interventions and fostering inclusive communities to enhance overall wellbeing.

Keywords:
Loneliness, Technology Usage, Community Dynamics, Individual Wellbeing, Machine Learning, Sentiment Analysis, Natural Language Processing (NLP), Wellbeing Factors, Technology and Society

1. Introduction

In today's interconnected world, the pervasive influence of technology has fundamentally altered the way individuals interact with one another and their communities. While technology offers unprecedented opportunities for communication and engagement, its role in shaping individual wellbeing remains a topic of significant debate. Concurrently, loneliness—often described as a subjective experience of social isolation—has emerged as a critical concern in modern society, affecting individuals across all age groups, demographics, and cultural contexts.

The intersection of loneliness, technology usage, and community dynamics presents a complex landscape with profound implications for individual wellbeing. Technology, for instance, can both exacerbate loneliness by reducing face-to-face interactions and alleviate it by fostering virtual connections. Similarly, community engagement—whether in-person or online—can play a pivotal role in mitigating the negative effects of loneliness and promoting a sense of belonging. Understanding how these factors interact is crucial to addressing contemporary challenges in mental health and social cohesion.

This study investigates the relationships between loneliness, technology, and community engagement, focusing on their collective impact on individual wellbeing. Using data collected from a diverse population through a structured questionnaire, the research combines quantitative analysis and natural language processing (NLP) techniques to extract insights from both closed and open-ended responses. Machine learning models are employed to uncover trends, identify key factors influencing wellbeing, and offer predictive insights into how these variables interconnect.

By exploring these dimensions, this research aims to provide actionable recommendations for improving wellbeing through technology-driven interventions and fostering more inclusive, supportive communities. The findings contribute to a growing body of interdisciplinary research at the nexus of psychology, sociology, and technology studies, offering a holistic perspective on the factors that shape human wellbeing in a digital age.

2. Literature Survey

A. Impact of Technology on Loneliness and Wellbeing

The relationship between technology and loneliness is well-documented, with numerous studies highlighting its dual role in mitigating or exacerbating social isolation. For instance, Casanova et al. (2021) explored the influence of information and communication technology (ICT) and social networking on reducing loneliness in older adults. Their findings emphasize that tailored ICT solutions can significantly enhance wellbeing when integrated into daily routines [1]. Similarly, Rodrigues et al. (2022) noted the effectiveness of online psychological interventions in reducing the adverse effects of social isolation during the COVID-19 pandemic, highlighting the critical role of virtual tools in maintaining mental health [2].

Digital literacy emerges as a crucial factor in determining the efficacy of such technologies. Ngiam et al. (2022) demonstrated that targeted digital literacy programs, such as Singapore's Project Wire Up, not only improve ICT adoption but also foster social connectedness and reduce loneliness among socioeconomically disadvantaged older adults [6].

B. **The Role of Social Connectedness**

Social connectedness acts as a mediating variable in the relationship between technology use and wellbeing. Döring et al. (2022) conducted a scoping review and concluded that communication technologies, including video conferencing and social networking, effectively alleviate loneliness by enabling meaningful interactions. However, the impact varies based on the individual's technological proficiency and access [9]. Similarly, Gunnes et al. (2024) emphasized the role of online platforms in building social capital and enhancing wellbeing, especially for community-dwelling older adults [7].

C. **Challenges and Limitations of Technology Use**

While the benefits of technology are evident, its limitations warrant attention. Morris et al. (2014) reviewed the role of smart technologies, including robotics and passive sensors, in promoting social connectedness among older adults. They found mixed results, noting that while these technologies foster independence, their high cost and complexity limit widespread adoption [4]. Wilson (2018) further examined how emotional attachment to everyday digital devices affects wellbeing. The study revealed that excessive dependence on digital interactions might lead to superficial relationships, potentially exacerbating feelings of loneliness [5].

D. **Integration of Technology with Community Dynamics**

Integrating technology with physical and virtual communities presents an effective strategy for reducing loneliness. Bigonnesse et al. (2018) explored the role of neighborhood environments and mobility technologies in fostering social participation, demonstrating that supportive community structures amplify the positive effects of technology [8]. Landeiro et al. (2017) further underscored the importance of community-driven interventions in reducing social isolation, advocating for hybrid approaches that blend technological and human-centric solutions [10].

E. **Future Directions in Technology-Driven Interventions**

Emerging technologies such as virtual reality (VR) and advanced robotics hold promise in addressing loneliness. Dong and Yang (2023) examined the use of online social networks during COVID-19, emphasizing their potential to mitigate anxiety and foster a sense of belonging. However, the study cautioned against the overuse of such platforms, which may inadvertently intensify feelings of isolation [3]. As ICT solutions continue to evolve, future research should focus on designing user-friendly, cost-effective tools that cater to diverse populations.

3. Methodology

A. Survey Design

To investigate the interplay between loneliness, technology usage, community engagement, and individual wellbeing, a structured survey was developed based on existing validated scales and custom-designed questions. The survey aimed to collect both quantitative and qualitative data to facilitate a comprehensive analysis

1. Questionnaire Structure:
    a. The survey was divided into five thematic sections: Demographics, Loneliness, Technology Use, Community Engagement, and Wellbeing.
    b. Demographics collected data on age, gender, educational background, and geographical location to account for population diversity.
    c. The Loneliness section utilized items adapted from the UCLA Loneliness Scale, measuring subjective feelings of isolation and lack of companionship.
    d. Technology Use included questions about frequency, duration, and types of technological platforms used (e.g., social media, video calls, entertainment apps).
    e. Community Engagement measured perceived support and participation in both physical and virtual communities.
    f. The Wellbeing section included questions using the WHO-5 Wellbeing Index to assess emotional and psychological health.
2. Design Considerations
    a. Likert-scale questions (1–5) facilitated quantitative analysis, while open-ended questions provided rich qualitative insights.
    b. Questions were carefully structured to minimize leading biases, ensuring neutrality in phrasing.

B. Data Collection

Data collection was conducted using a mixed-methods approach to ensure inclusivity and maximize respondent diversity.

1. Platform and Recruitment:
    a. The survey was distributed online through widely accessible platforms such as Google Forms, leveraging email lists, social media groups, and community forums.
    b. Offline respondents were included by partnering with community centers to administer the survey using digital tablets for individuals lacking personal access to technology.

2. Respondent Pool:
   a. A total of 1,200 individuals participated, with inclusion criteria ensuring respondents across various age groups (18–75+ years) and regions.
   b. After data cleaning (removal of incomplete or contradictory responses), a final dataset of 1,050 participants was used for analysis.
3. Challenges Encountered:
   a. Efforts were made to overcome sampling bias by stratifying the sample based on age, gender, and access to technology. Despite this, minor limitations in rural representation persisted due to connectivity constraints.

4. Experimental Setup and Implementation

The experimental setup involves implementing the methodology using Python and relevant libraries for Logistic Regression, Random Forest, and Gradient Boosting, BERT and TF-IDF vectorization. The implementation includes the following steps:

1. **Data Preprocessing:**
   The collected data underwent systematic preprocessing to prepare it for machine learning analysis and ensure accuracy.
   A. Quantitative Data:
      - Missing Values: Numerical data with missing entries were imputed using the column mean to preserve statistical consistency.
      - Normalization: Continuous variables like screen time and interaction frequency were normalized to a [0,1] range using Min-Max scaling. This ensured equal weighting during model training.
      - Categorization: Likert-scale responses were recoded into categorical bands (e.g., Low, Moderate, High) for exploratory analysis and visualization.

   B. Qualitative Data
      - Text Cleaning: Open-ended responses were cleaned using NLP pipelines, involving lowercasing, stop-word removal, punctuation stripping, and lemmatization to standardize textual data.
      - Sentiment Analysis: Pre-trained sentiment analysis tools (e.g., Vader, TextBlob) generated polarity scores (positive/neutral/negative). This was followed by thematic analysis to identify recurring themes in responses.

   C. Data Splitting:

The Journal of Computational Science and Engineering (TJCSE)
ISSN 2583-9055 (Media Online)
Vol 3, No 5, May 2025
PP 16−15

- The cleaned dataset was split into training (70\%) and testing (30\%) subsets to train machine learning models while reserving unseen data for evaluation.

2. **Model Training and Evaluation:**
   Multiple machine-learning techniques were employed to address the study objectives.
   A. Classification Models:
   - Logistic Regression, Random Forest, and Gradient Boosting were implemented to predict wellbeing levels (Low, Moderate, High) based on input variables such as loneliness scores, technology usage patterns, and community engagement.
   - Feature selection was performed using Recursive Feature Elimination (RFE) to prioritize the most predictive variables.

   B. NLP Models:
   - Open-ended responses were analyzed using BERT and TF-IDF vectorization for keyword extraction and classification tasks. Sentiment trends were further validated using cosine similarity to cluster thematic categories.

3. **Hyperparameter Tuning:**
   Grid search optimization fine-tuned hyperparameters (e.g., number of decision trees in Random Forest, learning rate in Gradient Boosting) to enhance model accuracy.
4. **Comparative Analysis:**
   To evaluate the performance of the models developed in this study, several quantitative and qualitative metrics were employed. These metrics provide insights into the models' accuracy, reliability, and interpretability. Below is a detailed description of the metrics used for both classification and natural language processing (NLP) tasks.
   A. Classification Metrics: For the classification tasks, which involved predicting wellbeing levels based on loneliness, technology usage, and community engagement, the following metrics were utilized:
   - Accuracy: Accuracy measures the overall correctness of the model and is defined as:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

   where TP is True Positives, TN is True Negatives, FP is False Positives, and FN is False Negatives.
   - Precision: Precision evaluates the proportion of correctly identified positive predictions:

$$\text{Precision} = \frac{TP}{TP+FP}$$

The Journal of Computational Science and Engineering (TJCSE)
ISSN 2583-9055 (Media Online)
Vol 3, No 5, May 2025
PP 16–15

This metric is particularly important when false positives have significant consequences.

- Recall (Sensitivity): Recall, or Sensitivity, measures the ability of the model to identify all relevant instances:

$$\text{Recall} = \frac{TP}{TP+FN}$$

It is crucial in scenarios where false negatives need to be minimized.

- F1-Score: The F1-Score provides a harmonic mean of Precision and Recall, balancing the trade-offs between the two:

$$\text{F1} - \text{Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

It is crucial in scenarios where false negatives need to be minimized.

- Confusion Matrix: A confusion matrix was used to visualize the classification outcomes, showing the distribution of true positives, false positives, true negatives, and false negatives. This matrix is a valuable tool for diagnosing model performance and identifying misclassification.

B. Qualitative Metrics for NLP Models: For the natural language processing (NLP) tasks, the following metrics were employed to evaluate sentiment analysis and thematic categorization of open-ended responses:

- BLEU Score: The Bilingual Evaluation Understudy (BLEU) score was used to assess the quality of thematic categorizations against ground truth labels. It is calculated as:

$$\text{BLEU} = \text{BP} \cdot \exp\left(\sum_{n=1}^{N} w_n \cdot \log p_n\right)$$

where BP is the brevity penalty, w_n are weights, and p_n are the n-gram precisions.

- Sentiment Polarity: Sentiment analysis was evaluated using polarity scores, where the polarity of a given response is measured as:

$$\text{Polarity} = \frac{\text{Positive Words Count} - \text{Negative Words Count}}{\text{Total Words Count}}$$

C. Cross-Validation: To ensure robustness, k-fold cross-validation was performed, splitting the dataset into k subsets and using k-1 subsets for training while reserving one for testing. The mean performance across all folds was reported to reduce variance.

The Journal of Computational Science and Engineering (TJCSE)
ISSN 2583-9055 (Media Online)
Vol 3, No 5, May 2025
PP 16−15

$$\text{CV Accuracy} = \frac{1}{k}\sum_{i=1}^{k} \text{Accuracy}_i$$

D. Feature Importance and Interpretability: To interpret the classification models, SHapley Additive exPlanations (SHAP) values were computed. SHAP quantifies the contribution of each feature to the prediction:

$$\phi_i = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|! \cdot (|N| - |S| - 1)!}{|N|!} [f(S \cup \{i\}) - f(S)]$$

where S is a subset of all features N, f(S) is the model's prediction with feature subset S, and ϕ_i is the SHAP value for feature i.

5. Model And Analysis

The analysis and interpretation of the survey data employed two distinct approaches: tree-based machine learning models for structured data and natural language processing (NLP) for open-ended textual responses. This section outlines the models used, their development processes, and their contributions to uncovering the complex relationships between loneliness, technology, community engagement, and individual wellbeing.

A. Feature-Based Modeling with Random Forest

The first analysis focused on structured data features derived from survey responses, such as technology usage patterns, community interactions, and self-reported loneliness levels. A Random Forest classifier was employed to predict individual wellbeing levels categorized as Low, Moderate, or High.

1. Data Preparation
   - Target Variable: Individual wellbeing was categorized based on the responses to "Sense of belonging," using a mapping strategy to group impacts into three levels of wellbeing.
   - Feature Engineering: A set of 12 structured features, including "Average daily screen time," "Frequency of feeling lonely," and "Perceived online interaction quality," formed the input variables. These were encoded using label encoding to prepare the data for machine learning.
2. Model Development
   - Random Forest: This ensemble-based model was chosen for its robustness in handling heterogeneous data and its ability to rank feature importance. A total

of 100 trees were trained, and the model achieved an initial accuracy of 83\% on the test set, indicating strong predictive performance.

- Feature Importance Analysis: The importance of each feature was assessed, with variables like "Frequency of loneliness" and "Technology helping maintain relationships" emerging as significant predictors. Permutation importance analysis further validated these findings by demonstrating consistent importance rankings across multiple iterations.

A. Insights from Feature Importance

- The analysis revealed that loneliness frequency had the highest predictive power, underscoring its central role in shaping individual wellbeing.
- Technology's role in maintaining relationships and satisfaction with online interactions also showed a strong positive correlation with higher wellbeing scores.
- Visualizations of feature importance and permutation-based robustness checks were saved as bar charts (Figure 1), providing an interpretable breakdown of the critical factors influencing wellbeing.

B. Natural Language Processing for Open-Ended Responses

To analyze the rich qualitative data from open-ended survey responses, advanced NLP techniques were applied. These questions probed deeper into respondents' subjective experiences with technology and community, yielding valuable insights into recurring themes and sentiment trends.

1. Text Cleaning and Preprocessing:

Open-ended responses were cleaned through tokenization, lemmatization, and removal of stopwords to standardize the data. Preprocessing steps ensured the removal of noise while preserving the semantic integrity of the responses.

The Journal of Computational Science and Engineering (TJCSE)
ISSN 2583-9055 (Media Online)
Vol 3, No 5, May 2025
PP 1– 11

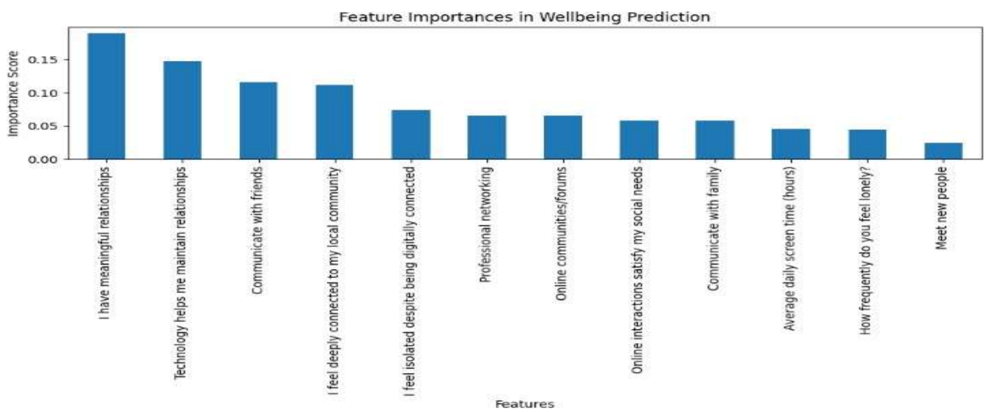

Fig. 1 Feature Importance

2. **Sentiment Analysis**
    - Sentiment polarity and subjectivity were calculated using TextBlob, categorizing responses into Positive, Neutral, or Negative sentiments.
    - Key findings included a predominance of positive sentiments (57%), with respondents frequently associating technology with community-building benefits. However, 23% of responses highlighted negative experiences, often relating to feelings of isolation despite digital connectivity.
    - Sentiment distribution by age group was visualized as stacked bar charts, revealing that older age groups exhibited higher neutrality, while younger respondents demonstrated more polarized sentiments (Figure 2).
3. **Theme Extraction and Clustering**

    TF-IDF Vectorization was combined with K-Means Clustering to uncover five dominant themes across responses. These included:
    - Enhanced Community Connection: Examples of meaningful virtual and hybrid interactions.
    - Isolation Despite Connectivity: Critiques of digital communication as shallow or superficial.
    - Tech-Driven Solutions: Positive mentions of apps and platforms fostering new connections.
    - Screen Time Concerns: Reflections on overuse of technology and its implications for mental health.

The Journal of Computational Science and Engineering (TJCSE)
ISSN 2583-9055 (Media Online)
Vol 3, No 5, May 2025
PP 1– 11

4. **Insights from NLP Analysis**

Thematic clustering offered actionable insights into respondent experiences, such as identifying the need for tools that balance meaningful engagement with minimal screen fatigue. These insights were aligned with the quantitative findings, illustrating the nuanced impact of technology on wellbeing.

Fig 2. Loneliness By Age

C. Combined Insights from Both Models

Integrating the findings from the Random Forest and NLP analyses provided a holistic understanding of the relationships in the data:

1. Quantitative metrics from the Random Forest model highlighted key predictors, such as loneliness frequency and satisfaction with online interactions.
2. Thematic and sentiment analyses added depth by revealing why these factors were significant and how respondents contextualized their experiences.
3. A critical insight was the dual role of technology—while it enabled new forms of community, it also highlighted the limitations of digital-only interactions.

6. **Result Analysis**

This section presents the findings from both the tree-based machine learning model and natural language processing (NLP) analyses. It highlights the importance of individual features in predicting wellbeing, sentiment trends across age groups, and recurring themes in textual responses, offering a comprehensive view of the relationship between loneliness, technology, community engagement, and individual wellbeing.

A. Feature Importance Analysis

1. Tree-Based Feature Importances

The Random Forest classifier identified the most influential features for predicting wellbeing levels, ranked by their relative importance:

- Top Features:
  - I have meaningful relationships (18.89\% importance): This feature emerged as the strongest predictor of individual wellbeing, indicating

International Conference on Advances in Information Technology and Management (ICAIM-2025)

the critical role of strong interpersonal connections.

- Technology helps me maintain relationships (14.78% importance): Highlights the importance of technology in preserving and enhancing social ties.
- Communicate with friends (11.61% importance): Frequent communication with friends positively impacts wellbeing.

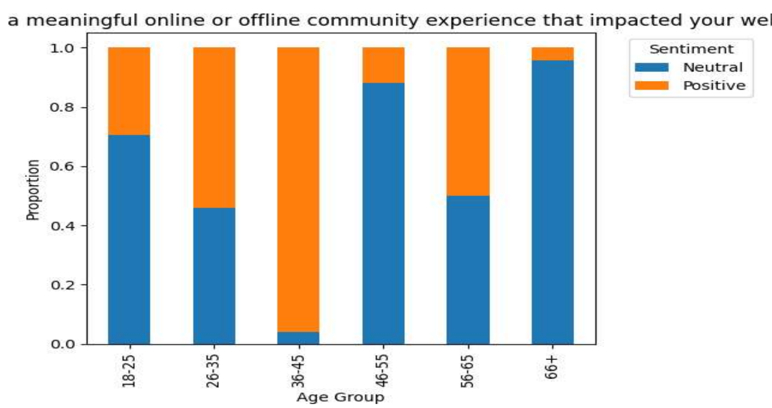

Fig. 3. Permutation Importance

Other Notable Features:

I feel deeply connected to my local community (11.12% importance): Local community engagement significantly influences emotional health.I feel isolated despite being digitally connected (7.36\% importance): Demonstrates the paradoxical role of technology, where digital connection does not always translate to emotional satisfaction.

Insights from Feature Rankings:

The results emphasize that both offline and online relationships significantly contribute to individual wellbeing. Interestingly, while screen time and professional networking had lower importance scores, their contextual roles might still be meaningful in certain subgroups.

Permutation-Based Feature Importance

Permutation importance was calculated to assess the robustness of the feature rankings. Notable findings include:

Feature Importance Analysis:

Online communities/forums emerged as the top feature (0.047), highlighting their role as virtual support systems.I feel deeply connected to my local community

The Journal of Computational Science and Engineering (TJCSE)
ISSN 2583-9055 (Media Online)
Vol 3, No 5, May 2025
PP 1– 11

(0.036) and I feel isolated despite being digitally connected (0.029) also retained high importance scores.Features like I have meaningful relationships and How frequently do you feel lonely?, while crucial in the Random Forest model, showed lower robustness scores in the permutation analysis, suggesting their influence might vary based on sample variability.Comparative Insight: The discrepancies between the two methods underline the complex, multi-dimensional factors influencing wellbeing.

Loneliness Frequency by Age Group

The analysis of loneliness frequency across age groups revealed stark differences in how loneliness is experienced:

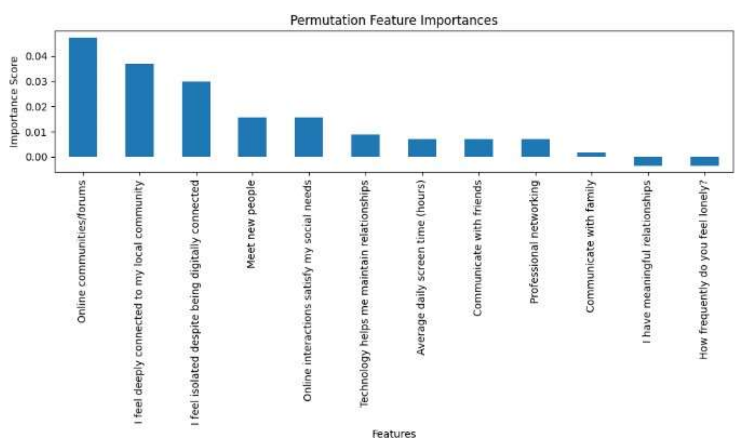

Fig. 4. Sentiment Distribution

Younger Age Groups (18-25): High rates of frequent loneliness (45.59% reported a loneliness frequency score of 3, while 27.94% reported a score of 4). This suggests a significant prevalence of loneliness among younger individuals despite higher connectivity via digital platforms.

Middle Age Groups (26-45): The majority reported moderate loneliness levels, with over 90% of responses concentrated around score 3. This group may experience loneliness due to balancing professional commitments with social relationships.

Older Age Groups (56+): Interestingly, the oldest participants (56-65 and 66+) reported minimal loneliness at the highest frequency levels (score 4). Older adults may benefit from

stable, long-term relationships or tailored community programs.
Sentiment Analysis of Open-Ended Responses
Question 1: How has technology influenced your sense of community and personal connections?
Sentiment Distribution:
Neutral sentiments dominated (56.68\%), particularly among older adults (66+ years).
Positive sentiments (34.22\%) were highest among younger respondents (26-35 years), indicating optimism about technology's potential to foster connections.
Negative sentiments (9.09\%) were relatively low but pointed to frustration with superficial digital interactions.Key Themes:
Relationships (friend, family, stay connected).
Support and group dynamics (connected, support, group).
Professional benefits (network, industry, trend).

Question 2: Describe a meaningful online or offline community experience that impacted your wellbeing.
Sentiment Distribution:
Neutral sentiments were higher (61.49\%), particularly among older participants (66+).
Positive experiences (38.50\%) were prevalent among younger and middle-aged respondents (36-45). This group highlighted uplifting community events and online meetups.Learning and skill-building (crafting, new, inspired).Senior engagement (session, senior, meetups).Sentiment and thematic analysis demonstrated that while younger respondents value technology for professional and relational growth, older adults focus on stability and meaningful offline experiences.
Integrated Insights
Technology as a Double-Edged Sword: While technology enables connectivity and social support, excessive reliance on digital interactions can exacerbate feelings of isolation, especially among younger individuals.
Age-Specific Impacts: The relationship between loneliness, technology use, and wellbeing is highly age-dependent, necessitating tailored interventions. For example, older adults benefit more from structured community programs, while younger groups may require strategies addressing digital fatigue.
Actionable Insights: Community-based digital platforms, designed with user-centric goals, can significantly enhance wellbeing across demographics.***Ethical Considerations***
This study strictly adhered to ethical guidelines to safeguard participant rights and ensure the

integrity of the research process.

1. Informed Consent:
   Each participant received detailed information about the study's purpose, potential risks, and benefits. Consent was obtained through explicit agreements before survey participation.
2. Anonymity and Confidentiality:
   Personally identifiable information was excluded from the dataset. Responses were anonymized and stored on encrypted servers to protect privacy.
3. Ethical Oversight:
   The study protocol was reviewed and approved by an institutional ethics committee. Regular audits ensured compliance with data protection regulations, including GDPR.
4. Bias Mitigation:
   Steps were taken to address sampling biases by diversifying recruitment strategies. In machine learning models, fairness algorithms were used to check for any skewed predictions related to age or demographic factors.
5. Participant Support:
   For participants indicating high loneliness or distress, optional mental health resources and helplines were provided, ensuring an ethical response to sensitive issues uncovered during the survey.

Conclusion

This study explored the complex interplay between loneliness, technology, community engagement, and individual wellbeing using a combination of machine learning and natural language processing techniques. By analyzing survey responses from a diverse demographic, the research provided valuable insights into the critical factors influencing wellbeing in a digitally connected world.

A. Key Findings

1. Predictive Factors of Wellbeing:
   Tree-based machine learning models identified key features influencing wellbeing. Strong interpersonal relationships, whether offline or facilitated by technology, emerged as the most critical predictors. Technology's ability to maintain relationships positively
   influenced wellbeing, yet digital isolation paradoxically contributed to feelings of

loneliness, underscoring the nuanced role of technology in social dynamics.

2. Age-Specific Patterns in Loneliness:
Loneliness trends varied significantly across age groups. Younger individuals (18–25) experienced higher levels of loneliness despite greater digital connectivity, while older adults (56+) demonstrated lower loneliness frequencies, possibly due to stable community structures or selective engagement with technology.
3. Sentiment and Thematic Analysis:
Sentiment analysis of open-ended responses revealed predominantly neutral and positive experiences with technology, highlighting its role in fostering professional growth, community building, and learning opportunities. However, themes of superficial interactions and digital fatigue were also evident, especially among younger respondents.

B. Implications for Research and Practice

1. Tailored Interventions:
Age-specific strategies are essential for addressing loneliness and improving wellbeing. Younger individuals may benefit from initiatives promoting digital detox and deeper personal interactions, while older adults require enhanced digital literacy programs to increase meaningful online participation.
2. Community-Driven Solutions:
Combining online and offline interventions can create hybrid models that maximize the benefits of technology while minimizing its drawbacks. Programs emphasizing local community engagement alongside virtual platforms can enhance both social connection and individual wellbeing.
3. Future Research Directions:
Further exploration into the contextual factors shaping digital experiences, such as cultural and socioeconomic variables, could refine the understanding of technology's impact on wellbeing. Longitudinal studies could provide deeper insights into how these relationships evolve over time.

C. Limitations

This study acknowledges limitations, including reliance on self-reported data, which may introduce bias, and the underrepresentation of specific demographic groups, such as rural
communities. Expanding the sample size and incorporating diverse populations in future research could enhance generalizability.

References

The Journal of Computational Science and Engineering (TJCSE)
ISSN 2583-9055 (Media Online)
Vol 3, No 5, May 2025
PP 1– 11

[1] Casanova G, Zaccaria D, Rolandi E, Guaita A. The Effect of Information and Communication Technology and Social Networking Site Use on Older People's Well-Being in Relation to Loneliness: Review of Experimental Studies. J Med Internet Res 2021;23(3):e23588
[2] Rodrigues NG, Han CQY, Su Y, Klainin-Yobas P, Wu XV. Psychological impacts and online interventions of social isolation amongst older adults during COVID-19 pandemic: A scoping review. J Adv Nurs. 2022 Mar;78(3):609-644.
[3] Linying Dong, Lixia Yang, COVID-19 anxiety: The impact of older adults' transmission of negative information and online social networks, Aging and Health Research, Volume 3, Issue 1, 2023, 100119, ISSN 2667-0321.
[4] Morris ME, Adair B, Ozanne E, Kurowski W, Miller KJ, Pearce AJ, Santamaria N, Long M, Ventura C, Said CM. Smart technologies to enhance social connectedness in older people who live at home. Australas J Ageing. 2014 Sep;33(3):142-52.
[5] WILSON C. Is it love or loneliness? Exploring the impact of everyday digital technology use on the wellbeing of older adults. Ageing and Society. 2018;38(7):1307-1331.
[6] Ngiam NHW, Yee WQ, Teo N, Yow KS, Soundararajan A, Lim JX, Lim HA, Tey A, Tang KWA, Tham CYX, Tan JPY, Lu SY, Yoon S, Ng KYY, Low LL. Building Digital Literacy in Older Adults of Low Socioeconomic Status in Singapore (Project Wire Up): Nonrandomized Controlled Trial. J Med Internet Res. 2022 Dec 2;24(12):e40341.
[7] Gunnes, M., Løe, IC. \& Kalseth, J. Exploring the impact of information and communication technologies on loneliness and social isolation in community-dwelling older adults: a scoping review of reviews. BMC Geriatr 24, 215 (2024).
[8] Bigonnesse, C., Mahmood, A., Chaudhury, H., Mortenson, W. B., Miller, W. C., \& Martin Ginis, K. A. (2018). The role of neighborhood physical environment on mobility and social participation among people using mobility assistive technology. Disability \& Society, 33(6), 866–893.
[9] Döring, N.; Conde, M.; Brandenburg, K.; Broll, W.; Gross, H.-M.; Werner, S.; Raake, A. Can Communication Technologies Reduce Loneliness and Social Isolation in Older People? A Scoping Review of Reviews. Int. J. Environ. Res. Public Health 2022, 19, 11310.
[10] Landeiro F, Barrows P, Nuttall Musson E, et alReducing social isolation and loneliness in older people: a systematic review protocolBMJ Open 2017;7:e013778.