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Utilising Machine Learning for Better Mental Health and Decision Making: A Case Study of Timebanking UK

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Abstract. This study explores how the integration of predictive models with machine learning and natural language processing can optimise community-based service operations, using Timebanking UK as a case study. The research evaluated these models in terms of their effectiveness in enhancing service matching, automating text classification, and improving interaction quality. Additionally, the study addressed privacy concerns through the use of synthetic data generation. The findings indicate that data-driven approaches can streamline service delivery, mitigate social isolation, and foster community engagement. This provides a framework for the broader application of predictive models within community and health systems.

Keywords. Social Wellbeing, Predictive Analytics, Machine Learning, Mental Health, NLP, Timebanking

1. Introduction

Community-based services are essential for enhancing mental health and well-being by fostering social cohesion, mutual support, and collaborative engagement within neighbourhoods and cities. These services encourage community members to share resources, skills, and time, creating inclusive environments that directly contribute to improved mental health outcomes [1]. Timebanking [2], a unique exchange model where time is used as currency, exemplifies this approach by enabling individuals to earn credits through service contributions, which can be redeemed for assistance from other members. This reciprocal system addresses practical needs while strengthening social bonds, reducing isolation, and promoting a sense of purpose and belonging, making it a prime candidate for integration into intelligent health systems. As health systems transition to integrated, data-driven frameworks, predictive models for community services like Timebanking could enhance patient-centred care [2]. Timebanking UK, with its extensive network,

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[2]https://timebanking.org/

represents a valuable source of non-clinical health data that offers insights into social determinants of health [3]. Integrating predictive analytics from Timebanking into NHS datasets could help anticipate community service needs [4,5], inform holistic care plans [6], and support proactive health strategies [7,8,9] to address social isolation and promote well-being at both individual and community levels.

The research presented in this paper uses Timebanking as a case study to analyse the efficacy of integrating predictive models and how machine learning and natural language processing approaches might improve these systems. The study focused on examining the potential of such models for integration into healthcare systems by enhancing the matching of service demands and offerings, as well as the quality of interactions. The research demonstrates the value of leveraging predictive models to support more effective community and health service planning.

2. Methodology

TimeOnline2 [3] serves as the primary platform for capturing Timebanking interactions across the UK. The members create accounts to make requests for assistance or offer their services, and each transaction is logged to record the time spent on these activities. The data generated sheds light on community engagement, revealing the nature and impact of Timebanking exchanges. Furthermore, we focused on identifying and analysing primary attributes to gain a deeper insight into the dynamics of these exchanges. However, due to constraints related to privacy and confidentiality, we were unable to access detailed descriptions of individual requests and offers. To address this issue, synthetic data was generated using ChatGPT [4], which created realistic descriptions for both *offers* and *requests* by leveraging existing attributes such as *category*, *activity*, and *time exchanged*. This synthetic data maintained consistency with the original data structure while ensuring compliance with privacy guidelines. Moreover, specific guidelines were followed to generate high-quality synthetic data. The synthetic descriptions were designed to be unique, community-focused, and personalised, avoiding any corporate tone. Descriptions were alternated between requests and offers and were tailored to specify the type of activity and relevant skills. Terms like *"Timebanking Request"* and *"Timebanking Offer"* were replaced with phrases such as *"request for"*, *"seeking help"*, or *"help needed for"* making the descriptions more descriptive and contextually appropriate. The data preparation and analysis process involved multiple steps, including data cleaning, transformation, and feature engineering to derive meaningful insights. Additional attributes such as *Location_ID*, *City*, *County*, *Region*, and *Country* were generated based on the postcode data to support detailed geographical analysis and to enhance the contextual understanding of Timebanking interactions. A sample of the generated synthetic data is shown in Table 1.

[3] https://timebanking.org/software/
[4] https://chat.openai.com

Table 1. Sampled Timebanking Requests and Offers by Activity and Label

Date	Postcode	Category	Activity	Gave Time	Description	Label
13/11/2002	S41 7JH	Health and Wellbeing	Coffee & chat	2	Seeking assistance with cleaning and organizing a storage room.	Request
11/08/2019	PL5 4DD	Health and Wellbeing	Stress Management	2.5	Stress Management Techniques: Sharing techniques for managing and reducing stress..	Offer
26/07/2006	BA2 1DE	Health and Wellbeing	Exercise	48	48-minute Exercise Session.	Offer
14/04/2008	S41 7JH	Health and Wellbeing	Stress Management	2	Requesting Meditation Session: In need of a guided meditation session for relaxation and stress relief.	Request

3. Experiments and Results

Two experimental tasks were conducted: (1) a time series forecasting task and (2) a classification task. The time series forecasting task aimed to analyse and predict trends in Timebanking requests over time by examining interactions across different locations. The forecasting problem was formulated as a multivariate time series model, incorporating three key variables: the date, the number of requests, and the Location_id as an external factor influencing the predictions. This approach facilitated the modelling of Timebanking requests at various locations (i.e., different Timebanks). To ensure the robustness of the models, the stationarity of the data was tested using the Augmented Dickey-Fuller (ADF) test [10], which determines whether a time series maintains a constant mean and variance over time. The test yielded an ADF statistic of -29.22 and a p-value of 0, providing strong evidence that the time series was stationary. As a result, no additional transformations were required to prepare the data for time series modelling. Additionally, to evaluate the performance of machine learning classifiers, several experiments were conducted. The dataset was split into training and testing sets, with the training data used for model training and cross-validation, while the testing data was reserved for assessing forecast accuracy.

3.1. Performance Evaluation using Time Series Forecasting

Two time series forecasting models were implemented: SARIMAX and Prophet. Both models are well-suited for handling complex time series data, including scenarios with external variables. SARIMAX (Seasonal AutoRegressive Integrated Moving Average with eXogenous factors) is known for its robustness in capturing seasonal patterns [11], while Prophet is designed for handling missing data and outliers, making it suitable for forecasting real-world trends [12]. When comparing the performance of these models, SARIMAX achieved significantly better results. In contrast, Prophet showed higher error values, as shown in table 2. These results suggest that SARIMAX was more effective in capturing the underlying patterns of Timebanking requests compared to Prophet. However, a closer examination of the forecasted values revealed that both models struggled to accurately predict future Timebanking requests. The discrepancies in the forecasting accuracy may be attributed to data representativeness, model selection, or data limitations.

Table 2. Performance Comparison of SARIMAX and Prophet Models

Model	Mean Squared Error (MSE)	Root Mean Squared Error (RMSE)	Mean Absolute Error (MAE)
SARIMAX	52.078	7.216	2.191
Prophet	374.400	18.794	3.603

3.2. Performance Evaluation using classification algorithms

The classification task aimed to achieve two key objectives: (1) binary classification to differentiate between request and offer types, and (2) multiclass classification to categorise various activity types within the Timebanking data. The binary classification task utilised a dataset of 1,979 entries, comprising 1,048 labelled as requests and 931 as offers. For the multiclass classification, the same dataset was employed, with descriptions assigned to 27 distinct activity categories. The dataset was split into 80% for training and 20% for testing to evaluate the performance of the classifiers. Four models were chosen for the classification tasks: Naïve Bayes, Support Vector Machine, Decision Tree, and Random Forest. Each of these models was tested for its ability to categorise the input data based on the features provided. The F-measure was used as the primary evaluation metric to ensure a balanced assessment of model performance. For the binary classification task, all models performed exceptionally well, achieving high F-measure scores. These results indicate strong capabilities in distinguishing between request and offer types. For the multiclass classification task, the models exhibited slightly lower performance compared to the binary classification. Although the multiclass classification was more challenging due to the increased number of categories, the classifiers still maintained high levels of accuracy. Table 3 shows the performance of the classifiers for binary and multiclass classification tasks.

Table 3. Performance of the Classification Algorithms for the Binary and Multiclass Tasks

Classifier	Binary Classification (F-measure %)	Multiclass Classification (F-measure %)
Naïve Bayes	98.0%	92.2%
Support Vector Machine	98.2%	96.7%
Decision Tree	97.5%	92.7%
Random Forest	99.2%	95.7%

4. Conclusion and Future Work

This study utilised Timebanking as a case study to evaluate the impact of predictive models on community-based interactions. By leveraging machine learning and natural language processing techniques, the research demonstrated how service matching could be enhanced, categorisation automated, and interaction quality improved. Using several machine learning algorithms.The evaluation of classification models revealed that traditional machine learning algorithms, such as Random Forest and Support Vector Machine, are highly effective in classifying Timebanking data. Notably, Random Forest consistently achieved the highest F-measure scores in both binary and multiclass scenarios, highlighting its robustness and reliability. These results provide a strong foundation for future work in refining classification capabilities. Potential areas for improvement include hyperparameter tuning and the exploration of advanced models like deep learning architectures. Future research should also focus on enhancing the generalisability of models to better capture the complexities of Timebanking activities. Additionally, efforts could be made to integrate more sophisticated predictive models that enable better forecasting of service demands and community needs. These advancements would further support the development of a more inclusive, efficient, and data-driven approach to community and healthcare service planning.

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