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*AutoMAP*

*Smart Wearables for Depression: Toward Autonomous  
Mental Health Monitoring for the Elderly*

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NSW - 2007, Australia



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**AutoMAP**  
**Smart Wearables for Depression: Toward  
Autonomous Mental Health Monitoring for the  
Elderly**

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*A thesis submitted in fulfilment of the requirements  
for the degree of*

Doctor of Philosophy  
*in*  
Software Engineering

*by*

**Fiza Tariq Mughal**

*to*

School of Computer Science  
Faculty of Engineering and Information Technology  
University of Technology Sydney  
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## ABSTRACT

**D**epression has increasingly become a significant concern over the years, even more so since the start of the COVID-19 pandemic. In the first year of the pandemic, anxiety and depression increased by 25% in all populations. Many older-aged people believe that mental illness is not something that can be treated and is often stigmatized. More so, older-aged people often have an increased risk of other mental issues, misdiagnosis as general age-related deterioration such as general cognitive impairment, Alzheimer’s disease, or dementia. This increased dependence on others and loss of general socio-economic status increases the likelihood of depression. In older aged people, mental illness and other age-related conditions inevitably lead to caregiver burden and dependence. One approach to aid in potentially alleviating caregiver burden while allowing older-aged people to live alone, is the use of consumer grade smart wearables to monitor depressive tendencies.

Increasingly, studies are being conducted on emotion recognition using contemporary technologies, particularly smart wearables. There is however a lack of focus on older-aged people (65+ years) as the target demographic. When this cohort has been investigated, study materials consist of obtrusive on-body sensors or are administered in lab-based settings with external emotion stimulation. As such, these are inapplicable or less accurate in real-world settings.

This thesis aims to address the above issues by proposing AutoMAP - Autonomous

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Mental health monitoring for older Aged Persons - a framework that incorporates consumer grade smart wearables for implicit user input and machine learning to infer depressive tendencies in order to create this system, a framework was proposed based on a comprehensive literature review in the area of emotion recognition and machine learning. This literature review was conducted to develop a clearer overview of mental health issues around the world, particularly in older-aged people, and the current state of research in emotion recognition and smart technologies. Through an in-depth analysis of existing research, strengths and limitations of existing approaches were highlighted. An assessment of these strengths and limitations allowed for the refinement of the current research project, aiming to reduce some of the identified limitations. Second, a conceptual framework that provides autonomous mental health monitoring for older aged people was developed. Third, an experimental study was performed with mixed-design methods to validate the proposed framework. Lastly, data outputs from the experimental study were analysed to validate the feasibility of the framework. Activity data from wearable devices were used to train and evaluate machine learning models to assess their predictive performance toward depressive tendency detection.

Based on the above, a proof-of-concept platform was created that consisted of (1) implicit user input, (2) machine learning, and (3) emotion reporting infrastructure. Various machine learning models will be explored for predictive modelling on device data. This research aims to conceptualize, propose, and pilot the impact and potential applicability of AutoMAP. These findings can collectively build a foundation toward better mental health monitoring and independent living for older aged users.

## AUTHOR'S DECLARATION

I, *Fiza Tariq Mughal* declare that this thesis, submitted in fulfilment of the requirements for the award of Doctor of Philosophy, in *Software Engineering, Faculty of Engineering and IT* at the University of Technology Sydney, Australia, is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis. This document has not been submitted for qualifications at any other academic institution.

SIGNATURE: \_\_\_\_\_

[Fiza Tariq Mughal]

DATE: 30<sup>th</sup> June, 2022

PLACE: Sydney, Australia





## DEDICATION

*To my grandmother and mother for inspiring this project ...*



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2.48. IYKYK

## LIST OF PUBLICATIONS

### JOURNALS

1. **F. Mughal**, W. Raffe, P. Stubbs, I. Kneebone, J. Garcia, *Fitbits for Monitoring Depressive Symptoms in Older Aged Persons: Qualitative Feasibility Study*, **JMIR Publications (accepted)**.
2. A. O. Kingsley, U. G. Inyang, O. Msugh, **F. Mughal** and A. Usoro, *Recognizing facial emotions for educational learning settings*, **IAES International Journal of Robotics and Automation (accepted)**.

### CONFERENCES

3. **F. Mughal**, W. Raffe and J. Garcia, *Emotion Recognition Techniques for Geriatric Users: A Snapshot*, 2020 IEEE 8th International Conference on Serious Games and Applications for Health - **SeGAH '20 (accepted)**.
4. **F. Mughal**, W. Raffe, P. Stubbs and J. Garcia, *Towards depression monitoring and prevention in older populations using smart wearables: Quantitative Findings*, 2022 IEEE 10th International Conference on Serious Games and Applications for Health - **SeGAH '22 (accepted)**.

### OTHERS

5. **F. T. Mughal**, *Latest Trends in Human Activity Recognition and Behavioral Analysis using Different Types of Sensors*, 345th International Conference on Innovative Engineering Technologies - **ICIET (accepted)**.

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## LIST OF ABBREVIATIONS

AD	Alzheimer's Disease
API	Application Programming Interface
AutoMAP	Autonomous Mental Health Monitoring for Older Aged Persons
CSV	Comma Separated Value
ECG	Electrocardiogram
EDA	Electrodermal Activity
EEG	Electroencephalography
EMA	Ecological Momentary Assessment
EMG	Electromyography
ER	Emotion Recognition
ETL	Extract-Transform-Load
FTD	Frontotemporal Dementia
GSR	Galvanic Skin Response
GDS	Geriatric Depression Scale

## LIST OF ABBREVIATIONS

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HC	Healthy Controls
HRV	Heart Rate Variations
MDD	Major Depressive Disorders
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MSE	Mean Square Error
MCI	Mild Cognitive Impairment
MVPA	Moderate-to-vigorous Activity Minutes
NIA	National Institute on Ageing
R <sup>2</sup>	R-square
RF	Radio Frequency
REM	Random Eye Movement
RSP	Respiration
RMSD	Root Mean Square Deviation
RMSLE	Root Mean Squared Logarithmic Error
SKT	Skin Temperature
SR	Speech Recognition
VR	Voice Recognition
WHO	World Health Organization