

RESEARCH

Björn Friedrich

# Empowering Independent Living using the ICF

An Unobtrusive Home Monitoring  
Sensor System for Older Adults

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An Unobtrusive Home Monitoring  
Sensor System for Older Adults

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Oldenburg, Germany

The School of Medicine and Health Sciences of the Carl von Ossietzky University of Oldenburg accepted this thesis as partial fulfilment of the requirements for the degree and title of Doctor rerum naturalium (Dr. rer. nat.).

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## Abstract

This thesis introduces a system that continuously keeps track of the functional status of older adults through monitoring their behaviour, physical parameters, and mobility in their domestic environments in daily life. Functional decline in older adults can lead to a loss in independence and an increased need of care. As a consequence, moving to a nursing home may be indicated. Moving to a nursing home may have a negative impact on the three innate psychological needs of humans. For the purpose of enabling older adults independently living in their own homes for longer, the system links data from unobtrusive and privacy preserving ambient and wearable sensors to five items of the *International Classification of Functioning, Disability and Health* (ICF), developed by the *World Health Organization* (WHO), from three categories and measures their change over time. The linking was realised by one Deep Neural Network (DNN), linear regression models, and a new unsupervised concept drift detection algorithm which combined a Variational Autoencoder (VAE) with a statistical hypothesis test. Based on the information provided by the system, health care professionals can design individualised rehabilitation programmes and monitor their effect. Moreover, the activities of daily living where assistance is needed can be identified and pointed assistance can be provided. Data from 20 (pre-)frail older adults (aged  $\geq 75$ y) collected during a 10-month observational randomised pilot intervention study was used for evaluation. The DNN achieved an accuracy of 94.27 % and 95.79 % on predicting the *Short Physical Performance Battery* (SPPB) and *Timed Up & Go* (TUG) score respectively. The linear regression model was able to detect all significant weight changes related to malnutrition and all abnormal days were correctly recognised by the unsupervised concept drift detection algorithm and hence the system provides useful information for health care professionals.

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## Kurzzusammenfassung

In dieser Arbeit wurde ein System zur kontinuierlichen Beobachtung des funktionalen Zustands älterer Menschen im täglichen Leben entwickelt. Das System beobachtet das Verhalten, physische Parameter und die Mobilität im Bereich des täglichen Lebens. Funktionaler Abbau im Alter führt zu einer erhöhten Abhängigkeit bis hin zu einem notwendigen Umzug in eine Einrichtung des betreuten Wohnens oder ein Pflegeheim. Insbesondere letzteres kann negative Auswirkungen auf die drei psychologischen Grundbedürfnisse von Menschen haben. Das System kann in den häuslichen Umgebungen von älteren Menschen installiert werden, um es ihnen zu ermöglichen länger dort zu leben. Es verbindet Daten von Hausautomations-, Energie- und tragbaren Sensoren, die die Privatsphäre nur minimal beeinträchtigen, mit fünf verschiedenen Kategorien aus drei Kapiteln des *Internationale Klassifikation der Funktionsfähigkeit, Behinderung und Gesundheit* (ICF) der *Weltgesundheitsorganisation* (WHO). Die Kategorien und ihr Verlauf werden mit Hilfe eines tiefen neuronalen Netzes, einem Regressionsmodells und einem neu entwickelten Algorithmus, der ein probabilistisches neurales Netz mit einem statistischen Hypothesentest kombiniert gemessen. Diese Informationen kann geschultes medizinisches Personal nutzen, um individualisierte Rehabilitationsmaßnahmen zu konzipieren, einzuleiten und ihren Effekt zu überprüfen. Außerdem kann das System Situationen, in denen ältere Menschen Unterstützung benötigen, identifizieren, damit gezielt unterstützt werden kann. Mit den Daten von 20 über 75-jährigen und gebrechlichen Teilnehmern\*innen, mit Frailty Syndrom oder im Vorstadium (pre-frail), einer 10-monatigen randomisierten Interventionspilotstudie wurde das System evaluiert. Das tiefe neuronale Netz erreichte eine Genauigkeit von 94,27 % und 95,79 % bei der Vorhersage von *Short Physical Performance Battery* (SPPB) und *Timed Up & Go* (TUG) Ergebnissen und das Regressionsmodell war in der Lage alle signifikanten

auf Mangelernährung hindeutenden Gewichtsveränderungen zu erkennen. Außerdem konnte der neu entwickelte Algorithmus alle von der Norm abweichende Tage korrekt identifizieren. Die Ergebnisse haben gezeigt, dass es wertvolle Informationen für medizinisches Personal bereitstellt.



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