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In-silico systems for well-being: Artificial Intelligence based analysis of psychological, mental, functional and quality of life aspects of life after breast cancer treatment

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1. Introduction

Artificial Intelligence (AI) analytic methodologies have provided cutting edge solutions to a variety of scientific fields. Within the field of Health Care Sciences, AI including machine learning and deep learning, has a significant impact on diagnosis, drug development and also in enhancing personalized treatment pathways. Our study uses AI methodologies to explore a retroscpective data set of 200 breast cancer survivors from the the Davidoff Center at Rabin Medical Center, Israel, focusing on two different tasks:

A. To identify subgroups of patients regarding their *Mental Status, Quality of Life and Functionality,* using measurements of indicative psychosocial variables at distinct time points within the period of treatment and a 2 year follow-up period. The ultimate goal of this part of the analysis is to extract clusters of patients with similar characteristics, within each of the above variables, and consequently observe how such groups differ from one another and evolve over time. For linguistic simplicity we will refer to this part of our work as A-Type studies.

B. To identify latent class trajectories with respect to several psychological quantities of interest using data across different time blocks, and thereafter, test the ability of a variety of AI classifiers to predict the respective trajectories using *solely baseline data*. *In other words, after identifying the latent class trajectory of a given psychological variable within a 24-month period of study, we use it as a target label for prediction, this time using exclusively baseline data.* The motivation behind this type of analysis *(B-Type studies)* is to construct a framework under which the psychological outcome of a patient can be predicted using data at the time of diagnosis (baseline). *Given that such a framework is available, the adoption of targeted treatments, adapted to the needs of a particular patient right after diagnosis, is feasible*.

In relation to *A-Type* studies, we only present indicative results of our work. In the context of this short abstract, we exhibit cluster formations regarding *the Mental State* variable group at baseline (that is, patient data right after the diagnosis). However, a similar analysis has been conducted for 3,6,12 and 12 months after diagnosis.

In relation to *B-Type* studies, we only present the identified latent class trajectory of *EGO Resilience* psychological variable, along with classification performance metrics of the respective classifiers for this particular variable.

2. Methodology

Below we present the psychological variables included in the *Mental State* variable group. In subsections 2.1 and 2.2, a brief insight on our methodology is provided for A-type and B-type studies respectively.

i. CES-D : Depressive Symptoms
ii. PDS : Posttraumatic stress symptoms:
iii. CERQPOS / CERQNEG : Cognitive and emotion regulation (positive / negative regulation).
iv. PDS : Posttraumatic stress symptoms
v. PTG : Posttraumatic growth
vi. EGO : Ego Resilience
vii. SressTod / ResTod / HopeTod : Feeling Today: level of Stress Today / level of perceived resilience today / amount of hope for the future (0-7.7, continuously scaled, especially designed for the study).

2.1 A-Type studies overview

The study aimed at clustering identification-formation of patients at baseline with respect to the *Mental State* variable group and refers to a subgroup of 129 patients. Pre-processing steps included *imputation of missing values and feature standardization* techniques [1]. The clustering algorithm of choice was the *Hierarchical Clustering Linkage* algorithm, with *Complete-Linkage* method [2].

2.2 B-Type studies overview

Latent Class – Mixed Effects Regression Analysis was applied to identify distinct trajectory patterns with respect to the *EGO variable.* A wide variety of *demographic, medical and symptom-related variables* were used as predictors for the extraction of the latent classes as collected within the study cohort . Afterwards, several classifiers were implemented, aiming to predict the latent trajectory of the EGO Resilience variable, *using only baseline data.* Namely, the implemented classifiers consist of: *K-Nearest Neighbors Classifier (KNN), Decision Tree Classifier (DT), Random Forest Classifier (RF), Neural Network Classifier (NN).* Before fitting the data to our classifiers, along with the respective trajectory labels, all necessary pre-processing steps were executed [1].

3. Results and discussion

3.1 Clustering formation: results on a-type studies

The Hierarchical Clustering algorithm enabled us to identify *4 distinct clusters of patients at baseline*. Table 1 provides descriptive insight on the characteristics of each identified cluster.

TABLE 1: Cluster Identification and summary of the within-cluster variables' magnitude.

Clusters	Cluster Characteristics	Number of Patients
1	**High Values** : EGO Resilience / CERQPOS / CERQNEG **Medium-High / Medium-Low Values**: CES-D / PTG / ResTod / SressTod / HopeTod **Low Values** : PDS	10
2	**High Values** : CERQNEG / CERQPOS / CES-D /EGO Resilience / PDS / PTG / SressTod **Medium-High / Medium-Low Values** : HopeTod **Low Values** : ResTod	18
3	**High Values** : ResTod / HopeTod **Medium-High / Medium-Low Values** : CERQPOS / PTG **Low Values** : CERQNEG / CES-D / EGO Resilience / PDS / SressTod	3
4	**High Values** : CERQPOS/ EGO Resilience / HopeTod / PTG / ResTod **Medium-High / Medium-Low Values** : PDS / CERQNEG **Low Values** : CES-D / SressTod	98

3.2 Trajectory identification and prediction: b-type studies results

Figure 1 depicts the identified latent class trajectories of the EGO variable. Figure 2 provides insight on indicative classification metrics regarding the ability to predict the given trajectories with baseline data.

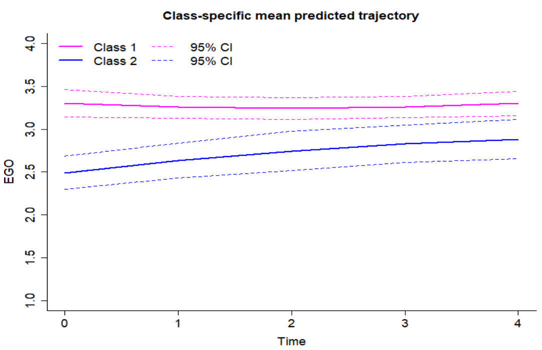

Figure 1: Identified Latent Classes for EGO

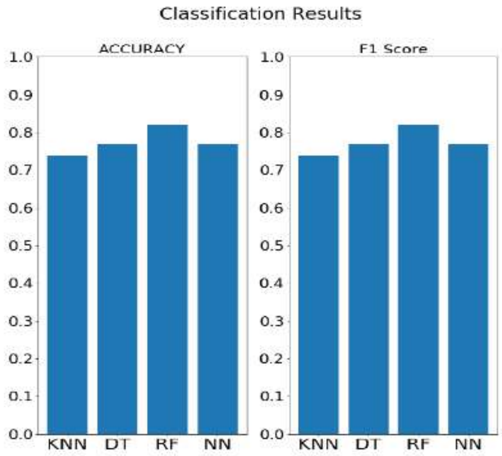

Figure 2. Classification Metrics for EGO

4. Conclusions

A-Type studies indicate that most patients exhibit positive mental status, with high values of positive emotional regulation, hope for the future and EGO Resilience at baseline. *(Cluster 4).* A considerable number of patients exhibit high values of stress and signs of posttraumatic symptoms at baseline, accompanied by lower values of perceived resilience *(Cluster 2).* Finally, *Clusters 1* and *3* are indicative of patients on a non-decisive mental state, possibly indicative of mixed feelings about the diagnosis. Concerning B-Type studies, our classifiers demonstrate a fairly high level of classification performance with respect to the prediction of the *EGO Resilience* latent trajectory, using exclusively baseline data. Thus, *our results indicate that beforehand design of targeted treatments according to a patient's predicted psychological progress is, indeed, feasible*. This suggests that personalized treatment is possible.

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