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How Health Literacy impacts Polytechnic of Leiria Students?

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Abstract

In 2021, a Health Literacy (HL) evaluation among university students revealed notable limitations in HL. To assess the general HL of populations comprehensively, the European HL Survey Questionnaire (HLS-EU-Q) was developed, encompassing 12 subdomains to provide a broad perspective on public health. In 2014, the questionnaire was adapted for use in Portugal, resulting in the HLS-EU-PT version, validated through a 16-question survey (HLS-EU-PT-Q16). Global HL and three domains' indexes and levels were determined, namely Healthcare (HC), Disease prevention (DP), and Health Promotion (HP). The HLSEU-Q16-PT assessment demonstrated satisfactory internal consistency, with 0.8834 Cronbach's alpha coefficient. In this study, an online survey distributed between 2020-2021 among Polytechnic of Leiria academia allowed data collection from various stakeholders, including 251 students, 109 professors, 15 researchers, and 55 other staff. From the 430 responses, 75 questions were analysed. The saved data was the focus of this work, regarding a thesis of the first edition of the master's in data science to analyse the 251 surveyed students and their HL. The results revealed that these students have lower HL index, and, in this case study, health area degree or school impacts HL.

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1. Introduction

Health Literacy (HL) originated through the pioneering work of Scott Simonds, a distinguished professor of Health Education at the University of Michigan's School of Public Health, during the 1970s. Simonds championed a paradigm shift in health education, advocating for a broader scope, the pivotal roles of institutions such as schools and families were identified for shaping social policy related to health. Also, the societal significance and the multifaceted influences were pointed out to shape individual health behaviours. [1]. The First International Conference on Health Promotion took place in Ottawa in 1986, in response to burgeoning global anticipation for advancements in public health initiatives. The Ottawa Charter for Health Promotion was introduced during this landmark event, providing a defining framework for health promotion endeavours. Within this charter, health promotion was articulated as "the process of empowering individuals to enhance control over and enhance their health. [2].

HL has several definitions: World Health Organisation (WHO) has the 1998 Health Promotion Glossary "HL implies the achievement of a level of knowledge, personal skills and confidence to take action to improve personal and community health by changing personal lifestyles and living conditions" [3] "the degree to which people can access, understand, appraise and communicate information to engage with the demands of different health contexts to promote and maintain good health across the life-course" [4].

HL is more than just Health promotion; it comprehends three main domains: Healthcare (HC), Disease prevention (DP), and Health Promotion (HP) [5]. The major stakeholders involved in HL were adult educators and literacy partitioners, community-based organisations, educators and health communicators, health professionals and government agencies, healthcare facilities, and the Academic community [6]. So, institutions such as the Polytechnic of Leiria academia are strong influencers on HL for the community, having a significant role in its development.

HL was examined in a systematic review. among university students, and to identify determinants related to HL. includes twenty-one research studies. The HL of university students was influenced by different variables (age, gender, number of semesters, course of studies/curriculum, parental education, and socioeconomic background) [7]. The long form of the European HL Survey with forty-seven questions (HLS-EU-Q47) and the short HLS-EU-Q16 were used for HL measurement among various bachelor's degree programs and different health study programs, except for medicine. There was compelling evidence for a relationship between HL among university students and age, the semester of study, gender, and course of studies. Still, the authors concluded that university students' HL seems to be insufficient and needs improvement [8].

HLS-EU-Q47-PT was applied to the Portuguese population throughout the country, including the autonomous regions, reaching 1004 individuals aged ≥ 16 years. This study revealed that 61% of the surveyed population has a problematic or inadequate general HL level. there is a downward trend in their levels when crossed with age groups - as age increases, the level of HL decreases. On the other hand, as education levels increased, the HL level increased, also [9]. In 2022, a HL study was published, in higher education students. 4801 students were surveyed using a quantitative, observational, and cross-sectional study, based on an online HLS-EU-PT survey disseminated in Portuguese universities. Almost half of the higher education students had inadequate or problematic levels of HL. It was found that HL levels do not differ in first-year and last year's students. However, in students from health-related courses, data revealed that last year's students had higher odds of having sufficient or excellent HL levels compared to a 1st-year student [10].

There are several tools for HL assessment; tools vary in their approach and design [11], [12]. A short version of the original 47 items tool, the HLS-EU-Q16 is more frequently used in population studies since it can be completed quickly and applied in several languages [13][11][14], [15], [16], [17] including in Portuguese [18]. The score of the HL index (range: 0-50), four levels of HL were defined for HLS-EUQ47: inadequate HL (scores 0-25), problematic HL (scores 25.1-33), sufficient HL (scores 33.1-42), and excellent (scores 42.1-50) [14], [18].

This study used collected data in the Polytechnic of Leiria academia about HL, using HLS-EU-Q16-Pt. An initial socio-demographics description was presented to detail and characterise the surveyed population [19]. Preliminary studies revealed that Polytechnic of Leiria students have lower HL scores than teaching staff [20]. The present work intends to get an insight into students' classification according to HL index results, whether they belong to the health area or attended health courses at the health higher school.

1.1. Structure

This manuscript has 4 sections, starting with this introduction, the database and methodology, the results, and the conclusion. The chapter Dataset and Methodology presents the dataset collected, the survey description, and the technologies and methodology used: In the results, the student HL index was presented, by descriptive statistics with data visualisation. The classification models were tested to explain if students HL allows distinguishing the students by area, health area or not, by having a health course and if they attend a health higher school. The conclusion presented the most relevant data mining and classification analysis.

2. Dataset and methodology

A quantitative, observational, and cross-sectional study was carried out based on an online survey disseminated in the Polytechnic of Leiria schools in 2020-21. The dataset had 431 records (lines) from the survey with answers to 28 questions including one dedicated to HLS-EU-Q16. The raw survey included the 16 questions of the HLS-EU-Q16-Pt. From the valid data, 430 responses, 75 questions were analysed, from the 251 students only 14 questions were considered, and their HL scores and levels.

2.1. Dataset

The survey was applied to characterise HL in Leiria academia. Automatically, it saved an ID, the initial timestamp, and the ending timestamp. The raw data had results recorded as numerical data, in general. Data mining was conducted after transforming the previous data into categorical format.

The survey data was collected between 8th December 2020 and 26th March 2021. The survey started with three initial questions, language, and statements to accept the participation and ensure an age of more than 16 years old. The first group of questions (Group 1) was the validated HLS-EU-Q16-Pt [18]. Group two had nine questions to characterise the inquired about personal issues; namely: age, gender, socioeconomic and well-being aspects (Group II), and professional occupation. The following two sections were exclusive to characterise students (Group III) or academic workers (Group IV), either teaching staff, research staff, and other staff [19], [20].

The students' subset had 251 answers to 28 questions. The student data was gathered from the three sections: the personal data (Group II), socio-demographics of students' roles, the characterisation of the students (Group III), and the calculated HL scores and levels from HLS (Group I). All data were saved in Excel format and the students' subset was created and saved.

2.2. Technology and methods

The Anaconda platform was used as an interactive terminal for using Jupyter Lab, which is the interactive development that runs in a web browser and allows you to edit and run code in Python for Data Mining. Data mining applied several packages and libraries. For example: pandas, numpy, seaborn, and sklearn.

The first step was to prepare the student's subset from the dataset reading, using the pandas library for excel format reading and save as data frame (equation 1).

```
dataset = pd.read_excel('HLdatasetLeiria1.xlsx', header=0)
student_subset = dataset[dataset['P12'] == 1] (1)
```

For data understanding several functions are used such as: .info(), .describe(), .columns(), .value_counts(), .value_counts(normalise=True). Descriptive statistics used mean, std calculation. Data visualisation through bar plot, and heatmaps was mandatory. Libraries such as matplotlib, pyplot, were used for data image creation. Data modelling involved several libraries and packages dedicated to learning modelling (sklearn, including individual for each model and sklearn.metrics). In this case, supervised learning models, these were tested to classify students regarding the HL index. Binary class models were Decision Tree (DT), K-Nearest Neighbour (KNN), Support Vector Machine (SVM), Gaussian Naive Bayes (GaussianNB), Logistic regression (LR), and Random Forest (RF). Its' evaluation was done to assess the models' quality, using accuracy, recall, F1-score, and AUC-ROC. The decision tree was created to classify students according to health area regarding the HL scores.

3. Results

The data mining and modelling were implemented using students' subsets of data. For these, HLS-EU-Q16-PT internal consistency was confirmed (Cronbach's alpha= 0.8656). First HL characterisation allowed us to highlight the lower scores of HL in Polytechnic students, compared to other roles analysed. The models that best explain the students' classification was SVM. The models enabled the classification of students from health-related area, and health higher school.

3.1. Students HL index

This population has 251 students, and the academic staff includes 109 professors, 15 researchers, and 55 other professionals. ANOVA allowed to verify the statistical evidence that differences between analysed groups' means are significant, for all the literacy scores (Fig. 1). For example, the global HL of professors is higher (35,33) than for students (33,02). The same is noticeable for other literacy scores (Table 1).

Table 1. HL index for all population regarding the role at Polytechnic of Leiria (N=430).

Population (n=430)	HeathCare (HC)		Disease Prevention (DP)		Health Promotion (HP)		Global HL	
	mean	± sd	mean	± sd	mean	± sd	mean	± sd
Role at Polytechnic of leiria								
Student (n=251)	33.65	± 7.56	31.73	± 8.14	33,43	± 8,91	33,02	± 7,02
Professor (n=109)	35.77	± 8.18	34.20	± 8.27	36,33	± 8,88	35,33	± 7,57
Researcher (n=15)	34.81	± 8.41	30.94	± 9.66	32,64	± 9,03	33,23	± 8,23
Other (n=55)	32.55	± 6.86	29.84	± 8.25	32,65	± 7,86	31,72	± 6,46
ANOVA (p-value)	0.0443		0.0098		0.0232		0.0103	

Regarding the Students subset, there was a perfect match of how well the ordered and standardised sample quantiles fit the standard normal quantiles with values of 1, for all domains HC, DP, HP, and global HL. Having this Shapiro-Wilk test results, a t-test was performed for several variables of interest within the students' responders' values. A descriptive analysis allowed us to state that the most frequent were problematic, and adequate classification (

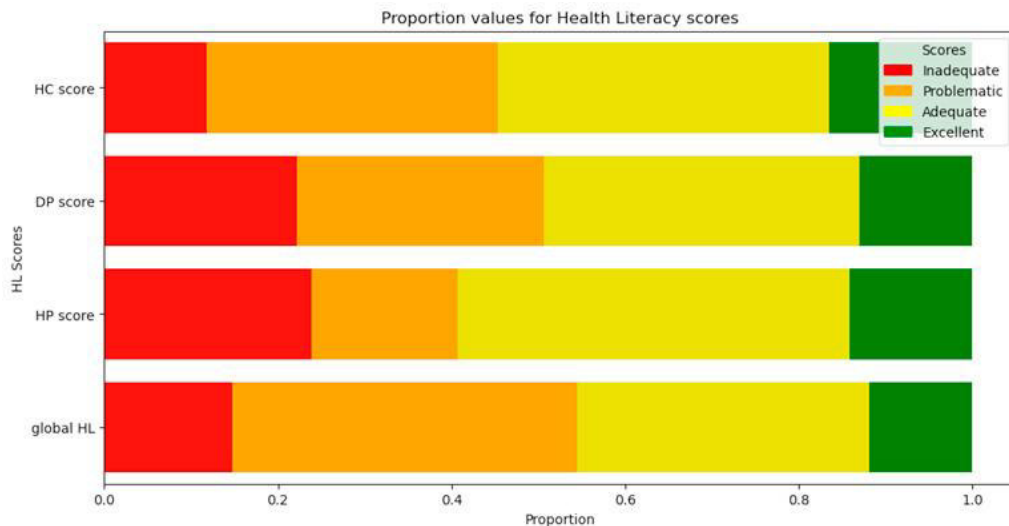


Fig. 1. Barplotting of students' HL index, namely Healthcare (HC), Disease Prevention (DP), Health Promotion (HP) and global HL.

Regarding HL scores, seventy-five students revealed an excellent score at HC (16.53%), 161 had an adequate score (38.14%), 42 had an inadequate score (11.02%) and 133 had a problematic (44.32%). For DP, there were fifty-four students with an excellent score (12.97%), 162 with an adequate score (36.40%), eighty-one with an inadequate score (21.34%), and 115 students with a problematic score (29.29%). For HP, sixty students revealed an excellent score (14.16%), 193 had an adequate score (45.13%), thirty-eight had an inadequate score (11.50%), and 99 had a problematic score (29.20%). In global HL, the majority, 170 revealed to have problematic scores (43.88%), then 150 students had an adequate score (33.76%), and only forty had an inadequate score (10.55%).

There were statistically significant differences in DP domain between students from health schools compared to other higher schools (t-test, P-value 0,03514). For HC there were no statistically significant differences (t-test p-value 0,9876), happening also with HP (t-test p-value 0,0957) and in global HL (t-test p-value 0,1971). Students of the health area (n=56) have higher mean values for all three domains and global HL (Table 2).

Table 2.HL index for students (N=251).

HL index	HeathCare (HC)		Disease Prevention (DP)		Health Promotion (HP)		Global HL	
	mean	± sd	mean	± sd	mean	± sd	mean	± sd
Degree area								
Health (n=56)	34.14	± 6.96	34.27	± 8.30	35,46	± 8,82	34,56	± 7,02
Other (n=195)	33.51	± 7.74	30.99	± 7.97	32,80	± 8,87	32,56	± 6,97
t-test (p-value)	0.646		0.0127		0.0443		0.0775	
Previous Health degree								
Health degree (n=20)	36.37	± 7.29	39.30	± 7.08	37,72	± 8,15	37,64	± 6,61
No health degree (n=231)	33.40	± 7.55	31.08	± 7.91	33,03	± 8,89	32,59	± 6,92
t-test (p-value)	0.125		<<0.001		0.0227		0.0030	
Parents area								
Health area (n=227)	33.62	± 7.60	31.58	± 8.17	33,66	± 8,75	33,01	± 7,02
Not health area (n=24)	33.95	± 7.35	33.18	± 7.90	31,15	± 10,34	33,10	± 7,17
t-test (p-value)	0.363		0.3634		0.0419		0.7068	

Having a previous higher degree in Health, the students present statistically significant differences of DP levels (t-test, P-value <0,001), HP (t-test, P-value 0,0227), and global HL (t-test, P-value 0,00296), compared to students that do not have previous Health degree. Only for HC levels, there were no statistically significant differences (t-test p-value 0,1254). There were no statistically significant differences for any of the domains of HL regarding the attribute of students having or not having their parents as health professionals (Table 2).

Students had a lower HL index; but when having a Health degree or having a previous health degree these impact the HL.

3.2. Classification models

In a broad approach, several models were tested to fit the student's data. The question was if the HL index allowed classifying students between areas. The classes defined were health area or any other area but not health. Comparing the various evaluation metrics, the SVM and Logistic regression better explain the classification of students. Accuracy and recall metrics highlighted the best results (>0.8) for SVM model.

Regarding students' higher school, accuracy and recall metrics highlighted the best results (>0.8) for SVM model. But precision stressed the decision tree as best model to distinguish if the students were from health school or other higher school, using the three domains and global HL index.

All the models had good (>0.5) accuracy, precision, recall and F1-score. The metric AUC-ROC only fit to assess binary classification models, but this one has lower values. AUC-ROC higher value (0.684) underlined the decision tree model to classify the students, from health higher school or not (Table 3).

Table 3. HL index was used to classify students regarding their area (health area or not) and if they attend health higher school or other school of Polytechnic of Leiria.

Classification using HL-index for students' health area or not						Classification using HL-index for students from health higher school or not				
Model	Accuracy	Precision	Recall	F1-Score	AUC-ROC	Accuracy	Precision	Recall	F1-Score	AUC-ROC
Decision Tree	0.704	0.775	0.704	0.733	0.552	0.750	0.809	0.750	0.770	0.684
K-Nearest Neighbour	0.704	0.721	0.704	0.712	0.452	0.636	0.668	0.636	0.651	0.477
Support Vector Mchine	0.841	0.707	0.841	0.768	0.583	0.818	0.669	0.818	0.736	0.288
Gaussian Naive Bayes	0.772	0.798	0.772	0.784	0.633	0.795	0.785	0.795	0.790	0.576
Logistic Regression	0.841	0.707	0.841	0.768	0.579	0.773	0.662	0.773	0.713	0.517
Random Forest	0.750	0.764	0.750	0.757	0.548	0.750	0.737	0.750	0.743	0.622

The decision tree model better explained various students' aspects differences, based on index features such as DP, HP, HC, and Global HL. The resulting decision tree provides a structured framework for data classification into distinct classes, students from health higher school.

Through a detailed analysis of the decision tree structure and its associated criteria, insights into the factors influencing health school classifications (Fig. 2).

The resulting decision tree comprises a series of decision nodes and leaf nodes, each representing a split based on specific feature values.

```

|--- DP_index <= 31.67
|   |--- HP_index <= 14.58
|   |   |--- class: Other
|   |   |--- HP_index > 14.58
|   |       |--- HC_index <= 38.49
|   |       |   |--- class: HealthSchool
|   |       |   |--- HC_index > 38.49
|   |       |       |--- class: HealthSchool
|--- DP_index > 31.67
|   |--- HC_index <= 46.43
|   |   |--- Global_HL_index <= 44.27
|   |   |   |--- class: HealthSchool
|   |   |   |--- Global_HL_index > 44.27
|   |   |       |--- class: Other
|   |--- HC_index > 46.43
|   |   |--- HP_index <= 47.92
|   |   |   |--- class: HealthSchool
|   |   |   |--- HP_index > 47.92
|   |       |--- class: HealthSchool

```

Fig. 2. Predicted decision tree using HL index of students to distinguish whether they were from health higher school or not.

The decision tree effectively partitions the dataset into distinct classes, including "HealthSchool" and "Other" based on created thresholds in the decision tree model.

Through a detailed analysis of the decision tree structure; features such as DP_index, HP_index, and HC_index play significant roles in determining health school students' classification.

Students with low DP score (31.67 or less) were mostly classified into "HealthSchool" if they had a moderate to high HP score (greater than 14.58) and HC scores, both higher and lower than 38.49.

For students with high DP scores, namely greater than 31.67, the classification hinges on their HC and Global HL index. If their HC score is 46.43 or lower, a high Global HL score (> 44.27) leads to a classification as "Other," while lower scores classify them as "HealthSchool". This does not seem very coherent with expected. But, when students' HC index values were above 46.43, individuals are consistently classified as "HealthSchool" regardless of their HP scores.

This decision tree model could help in understanding how different dimensions of health literacy contribute to students' classification. It emphasised the importance of different HL domains and their index thresholds in determining these classifications.

This decision tree analysis demonstrated to be a valuable tool for classifying health school, offering a structured approach for understanding the complex interplay between HL and students' school.

By leveraging features such as DP_index, HP_index, and HC_index, the decision tree model effectively categorises data into meaningful classes, providing actionable insights for academia stakeholders.

4. Conclusion

A HLS-EU-Q16-PT internal consistency was verified (Cronbach's $\alpha = 0,8834$), and after data transformation to comprehend the attributes, the students presented insufficient HL. Significant differences occur for all literacy scores according to the role. This corroborates previous studies. Only, students in the health area or those having a previous health course revealed statistical differences in HL index. There was a confirmation of expected lower HL among Students which revealed that having a previous health degree has a positive impact on the HL index, being statistically significant the difference for 3 domains, DP, HP and global HL.

Considering numerical HL index values of all three domains, HC, DP, and HP, and global HL, these values were used to train learning models, looking forward to identifying the more accurate classification learning model. Regarding the metrics used, the SVM models reveal better accuracy when classifying students' areas, and schools. But regarding AUC-ROC the Decision tree fits better to distinguish higher schools.

The decision tree provides a structured way to classify individuals based on their health literacy scores across various domains. The model highlights specific index thresholds for DP, HP, HC, and global HL, guiding the final classification into "HealthSchool" or "Other" groups. This approach allows for a nuanced understanding of how HL factors influence students' classification.

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