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A machine learning analysis of psychopathological features of Eating Disorders: a retrospective study

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Abstract

Background: The clinical presentation of Eating Disorders (EDs) is often characterized by a great phenotypic variability and by a substantial instability over time of diagnostic categories. For these reasons, it has been proposed a different approach to EDs, encompassing both their dimensional and categorical descriptions, in a lifetime perspective, namely the '*Anorexic-Bulimic Spectrum*' (ABS). Here we report a retrospective study with the interview built and validated for the assessment of ABS signs and symptoms, the '*Structured Clinical Interview for Anorexic-Bulimic Spectrum*' (SCI-ABS), administered together with the '*Mood Spectrum Self Report*' (MOODS-SR), a questionnaire able to assess sub-threshold mood spectrum dysregulations often comorbid with EDs signs and symptoms.

The main aim of the study was twofold: to assess and better characterize clinical phenotypes of EDs; to highlight potential lifetime sub-threshold mood dysregulations that might occur comorbid with EDs, and that patients might consider relevant to their *'subjective experience of illness'*. In order to obtain these goals, we decided to utilize a machine learning analysis.

Methods: two groups were recruited and compared, namely patients with EDs (n=53) and healthy controls (HC) (n=54). Both groups underwent psychological testing with MOODS-SR and SCI-ABS.

Results: in discriminating and classifying EDs individuals from HC, machine learning classifiers obtained an accuracy higher than 70%. Based on all variables considered, the analysis revealed that SCI-ABS *'Phobias'* domain (more in detail, '*Weight Gain Phobia*' total score), the '*Impairment and Insight*' item 5, ('*…your relationship with food was all you could think about?*') and the MOODS-SR item 154 ('*you were less sexually active than is typical for you?*') were the best psychological elements in discriminating EDs patients from HC (accuracy range: 72.90-86.92%). Given the large number of predictors, we run a supervised attributes selection procedure. The procedure yielded an accuracy of 90.65% in classifying EDs patients from HC.

Conclusions: the very high overall accuracy is indicative that the selected combinations of features capture the most important determinants in the discrimination of EDs patient's vs HC. The items selected by the machine learning analysis confirmed that an extreme polarization of ideas on weight and food control characterize the cognitive asset of EDs patients.

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1. Introduction

Eating Disorders (EDs), such as anorexia (AN) and bulimia nervosa (BN) are a group of chronic and potentially fatal psychiatric illnesses which are highly prevalent worldwide and afflict mainly female adolescents and young women (Martino et al., 2019; Miniati et al., 2018a, 2018b, 2019; Swanson et al., 2011; Ward et al., 2019). On the epidemiological level, the lifetime prevalence of EDs is around 8.4% (3.3-18.6%) for females and 2.2% (0.8-6.5%) for males (Galmiche et al., 2019). In the recent years, among the different types of EDs, AN seems to have increased in prevalence amongst younger girls (15-19), while the occurrence of BN might have decreased (Smink et al., 2012). Excessive concern and overestimation associated to body shape and weight, along with controlling eating behavior are considered AN and BN '*core psychopathological features*' (Cassano et al., 2003; Di Nardo et al., 2020; Hasan et al., 2018; Laporta-Herrero et al., 2018). Some studies have shown how BMI levels can be linked and influenced by certain personality traits, especially in the adolescent age group, where body uneasiness is widespread (Gugliandolo et al., 2020; Rosa et al., 2019; Ylmatz & Boso, 2019). Moreover, EDs usually worsen quality of life (QoL), anxiety levels, affectivity, and mortality rates (Ágh et al., 2016; Arcelus et al., 2011; Craparo et al., 2020; Johnson et al., 2001; Swinbourne et al., 2007). Individuals suffering from AN are particularly at risk, with an annual mortality rate around 5.10 deaths (95% CI, 3.99-6.14) per 1000 person-years, of which 1.3 deaths associated with suicide (Arcelus et al., 2011).

Furthermore, EDs clinical presentations are complex and inhomogeneous, varying from mildly abnormal eating to a life-threatening disorder (Grisset & Norvell, 1992; Grubb et al., 1993; Rikani et al., 2013; Striegel-Moore & Bulik, 2007; Troop et al., 1994). EDs are characterized, in most cases, by diagnostic instability, with a large proportion of patients who shifted from a diagnostic category to another one during their lifetime (Milos et al., 2005; Striegel-Moore, 1995), and by a chronic course that led to different levels of impairment. Unfortunately, as for different chronic conditions, EDs often lead to significant psychopathological consequences, such as anxiety and depression, as direct consequence of the high levels of stress prolonged over time (de Vos et al., 2017; Martino et al., 2019; Merlo, 2019; Mula et al., 2008; Palagini et al., 2016; Piccinni et al., 2012; Sauro et al., 2008; Veltri et al., 2012; Wonderlich et al., 2012; Yau & Potenza, 2013). Moreover, as with all chronic diseases, patients' QoL is severely affected (de la Rie et al., 2005). EDs impact many domains of life such as work, interpersonal relationships, and social functioning, which are all fundamental aspects of the modern concept of QoL (Ackard et al., 2013; Bamford & Sly, 2010). Several studies have found that severity of the EDs (ie. extreme dieting/binge eating), distress, and body mass index (BMI) are predictors of low QoL, outcome which does not appear to be moderated by gender (Bamford et al., 2015; Bentley et al., 2015; Hay, 2003; Mason et al., 2018; Mitchison et al., 2012; Wagner et al., 2016). In addition, Mitchison and colleagues (2015) found a bidirectional relationship between EDs severity and low health related QoL.

Recently, the boundaries of EDs have expanded, with a growing interest in their atypical, subclinical and/or sub-threshold forms (Fairburn & Walsh, 2002; Miniati et al., 2018a, 2018b). It is common, in the clinical practice, to evaluate subjects who are not fulfilling the diagnostic criteria for a full-blown or a 'typical' AN or BN, but that might have signs and symptoms interfering with dietary habits, correlated with significant levels of body dissatisfaction (Grange & Loeb, 2007). Along this line, a phenotypic dimensional description of the most important EDs has been proposed by Mauri and colleagues (2000, 2002), the '*Anorexia-Bulimia Spectrum*' (ABS). ABS was directed toward the full extent of signs, symptoms and traits experienced over the lifetime both by patients who fulfilled the DSM criteria for an EDs, and by subjects who might show their sub-threshold or incomplete forms.

With the purpose to assess eating spectrum characteristics, two instruments were validated, namely the Structured Clinical Interview for Anorexia-Bulimia Spectrum (SCI-ABS) and its self-administration version (ABS-SR) (Mauri et al., 2000, 2002). In this context, we believe that to obtain a clear understanding of the eating spectrum disorders phenotypes, it is pivotal to increase the detection of comorbid mood symptoms. Several empirical studies reported a large proportion of comorbidity between mood and eating disorders, that ranged from 24% to 90% and from 31% to 88% in BN and AN, respectively (GoMdart et al., 2007; McElroy et al., 2005). In order to enhance the phenotypic definition of EDs along with the reliability of spectrum disorder evaluation, we suggested a dimensional mood spectrum procedure, which had already demonstrated its clinical value (Miniati et al., 2018a, 2018b). Within the research project, it has been applied the Mood Spectrum Lifetime Questionnaire (MOODS-SR-Lifetime Version; Cassano et al., 1999; Fagiolini et al., 1999) and the ABS.

The aim of the present study was to explore if EDs patients could be accurately identified when compared to healthy controls, utilizing the results of the questionnaires administered. Clarifying the role of specific psychological domains and determinants in patients with EDs can allow a better understanding of the disorder, consequently the development of patient-tailored treatment. Therefore, in order to extract clinical details from the datasets collected, we applied the machine learning (ML) techniques. ML methods are not extensively used in the analysis of psychological data as compared to other fields. In fact, the scores measures obtained in the context of clinical and experimental psychology or in psychiatry have been traditionally analysed with more conventional statistical inferential techniques. Since the "*reproducibility*" or *"replicability* *crisis*" (Baker, 2016) in psychology was debated, an increasing interest in developing more efficient tools for analysing the results of psychological datasets has been put in place. Baker (2016) highlighted that one of the main sources of potential problem can be associated to the use of inferential statistics and its misunderstanding of p-values. The use of a procedure known as Cross Validation is usually a good procedure to measure how well a result may be replicable (Cumming, 2008). Indeed, while cross validation does not prevent the model to overfit, it estimates the true performance.

ML methods with the application of cross validations procedure have been already shown in a number of psychological and psychopathological studies that ML algorithms can enhanced the traditional psychometric testing to predict patient outcomes in different domains (Ferrarese et al., 2021; Mazza et al., 2019a, 2019b; Orrù et al., 2012, 2020a, 2020b; Pace et al., 2019; Sartori et al., 2017).

2. Materials and methods

2.1 Participants

One hundred and seven Italian-Speaking female participants were recruited and analyzed. The sample consisted of two groups: patients with DSM-IV eating disorders (EDs) (n=53; mean age: 25.25±4.63 years; mean BMI 17.87±3.54) and healthy controls (HC) (n=54; mean age: 26.46±5.49 years; mean BMI 21.31±2.48). Both groups were recruited within the framework of a multi-center study, described in detail by Mauri et al., (2000). Patients belonging to the EDs group were assessed according to the DSM-IV criteria, as data were collected before the publication of the DSM-5. The inclusion criteria were as follows: female inpatients and outpatients with EDs, regardless of the specific SCID-I diagnosis, consecutively admitted to the Institute of Psychiatry of the University of Pisa. For both groups, the exclusion criteria were: (1) a primary diagnosis of schizophrenia; (2) schizoaffective disorder; (3) bipolar disorder (I and II); (4) concurrent alcohol or substance abuse during the 3 months before recruitment; (5) severe uncontrolled medical illnesses.

2.2. Materials

The psychological assessment included the following inventories: The Lifetime Mood Spectrum Self-Report (MOODS-SR) (Dell'Osso et al., 2002) and the Structured Clinical Interview for Anorexic-Bulimic Spectrum (Mauri et al., 2000).

The MOODS-SR is the lifetime self-report version of the Structured Clinical Interview for Mood Disorders (SCI-MOODS) (Fagiolini et al., 1999). MOODS-SR investigates the presence of manic/hypomanic and depressive symptoms, disturbances in rhythmicity and vegetative functions and its psychometric properties have been widely validated (Ioannou et al., 2016).

The SCI-ABS is conceptually organized in nine domains: (1) attitudes and beliefs; (2) weight history; (3) self-esteem and satisfaction; (4) phobias (including 4 sections: A. Body dissatisfaction; B. Weight gain phobia; C. Secondary social phobia; D. Visceral perceptions); (5) Avoidant and compulsive behaviors; (6) Weight Maintenance (including 2 sections: A. Dietary habits; B. Physical activity); (7) Eating dyscontrol; (8) Associated features and consequences (including 3 sections: A. Impulse control; B. Personality; C. Physical consequences); (9) Impairment and Insight (including 2 sections: A. Impairment; B. Level of insight).

2.3 Procedure

The present study was approved by the Hospital of Pisa Ethics Committee in accordance with the Declaration of Helsinki. In order to take part to the study, all participants gave their written informed consent.

2.4 Statistical and Machine learning data analysis

Data analysis has been carried out using the Statistical Package for Social Sciences (SPSS Inc., Chicago, IL) and Weka 3.9 (Hall et al., 2009). T-test has been conducted and according to the t values obtained, along with the sample size of both groups considered (EDs, n=53; HC, n=54), the effects sizes (d) have been determined using Borenstein's formula (Borenstein et al., 2009). The extent of the effect sizes was interpreted according to Cohen intervals (Cohen, 1988).

With the aim to assess the most important features in the classification of EDs patients and HC, the variables used to create ML models were: 1) age; 2) education; 3) SCI-ABS; 4) MOODS-SR. We excluded from the classification the body max index (BMI) as an obvious predictor in eating disorders. In order to have a lower rate of bias, we used the k-fold cross validation technique, which randomly divide the dataset into k folds of equal size (approximately), where the value for k was set to 10 (k=10).

Once this procedure was performed, we run the main classifiers. After that, a preliminary procedure called "attribute selection" was applied with the purpose of obtaining the most informative variables (attributes) (Hall, 1988). Through this procedure, it was possible to exclude the variables which did not provide a distinction between the EDs and HC groups. Furthermore, using the JRIP algorithm (Cohen, 1995) we pinpointed the most important predictors for the classification process and the best rule which correctly classifies the individual in the two groups (EDs vs HC).

3. Results

Means and standard deviations for the variables considered are shown in **Table 1a**. As previously mentioned, t-test has been carried out and the effect sizes have been determined using Borenstein's formula. According to Cohen's intervals (Cohen, 1988), the questionnaire measures examined in the study have displayed effect sizes from small (interval: 0.2 - 0.4) to large effect (interval: 0.8 - ≥ 1). The effect sizes (d) and t-test values are shown in **Table 1b**.

Table 1a and 1b. Demographic features and tests performance (EDs and HC groups) and Variables considered (t-test values and effect sizes).

	Group	N	Mean	Std. dev
Age	HC	54	26.46	5.497
	EDs	53	25.25	4.632
BMI	HC	54	21.3137	2.48015
	EDs	53	17.8706	3.54406
ABS total score	HC	54	27.83	23.346
	EDs	53	69.96	24.964
MOODS Total Score	HC	54	48.04	36.220
	EDs	53	78.64	37.259

Table 1b. Variables considered, t-test values and T effect sizes (d)

Variables	Student Value	T Effect size (d)1
Age	1.24	0.24
BMI	5.83	1.13
ABS total score	-9.02	-1.74
MOODS Total Score	-4.31	-0.83

3.1.1. The accuracy of classification between EDs and HC.

In a psychological and psychiatric-clinical setting, the application of SCI-ABS and MOODS-SR inventories is particularly useful if the clinician is able to accurately identify which are the main aspects able to distinguish individuals with EDs from HC. The objective here is to find the best parameters that may distinguish EDs and HC individuals. For the purpose to reach this aim, we applied ML technique and relevant algorithms. During the classification, the variables exhibiting optimal efficiency (removing the body max index, BMI) in classifying the individual within the EDs group or HC group have been identified through JRIP rule (Cohen, 1995) and its cut-offs. JRIP yielded an accuracy of 74.77 % in correctly classifying the subject in the two groups and the rules (n.3) were the following:

If the total score of the SCI-ABS is ≥ 50, then the individual is classified as an EDs subject.

If the SCI-ABS domain 1 (attitudes and believes) total score is ≤0 and item 31 of the MOODS-SR is ≥1, then the individual is classified as an EDs subject.

If the previous two roles are not applicable, then the individual is classified as an HC subject.

The reported set of rules derived not from the greatest classifier, but it provides a best comprehension of the assumption. The accuracies in classifying EDs patients and HC were 80% and 70%, respectively. The reported set of decision rules results in high accuracy in classifying EDs patients (42/53; accuracy=80%) and HC (38/54; accuracy=70%), AUC=0.79 (d=1.14) and F1=0.75.

As reported by Orrù et al. (2020b), there is a trade-off between interpretability and accuracy. Usually interpretable classifiers (based on decision rules) are rarely the most accurate and the most accurate classifiers are rarely the most transparent to intuition.

The accuracies demonstrated by 5 main classifiers, using k-fold cross validation technique (k=10) are shown in **Table 2**. The classifiers used were run with default parameters of Weka software. As can be seen, the most accurate classifier on our dataset is Random Forest.

Table 2. The correct classification achieved by the different classifiers measured by: accuracy, AUC, F1.

Classifier	Accuracy (%)	AUC	F1	Correct Classification	
Naïve Bayes	79.44%	0.86 (d=1.53)	0.79	EDs 43/53	HC 42/54
Logistic Regression	70.09%	0.79 (d=1.14)	0.70	EDs 36/53	HC 39/54
Simple Logistics	80.37%	0.87 (d=1.59)	0.80	EDs 42/53	HC 44/54
Support Vector Machine	83.18%	0.83 (d=1.35)	0.83	EDs 43/53	HC 46/54
Random Forest	85.05%	0.88 (d=1.66)	0.85	EDs 46/53	HC 45/54

3.1.2. Classification between EDs and HC using the preliminary selection of most informative variables.

With the purpose to detect the most informative domains and subdomains based on the inventories administered, we run the classifiers using as input the best parameters that may distinguish EDs and HC. Using as an input, a preliminary selection of the most informative attributes (Hall, 1998), the classifications accuracies were significantly high. JRIP algorithm, this time was able to correctly classify the subject in the two groups (EDs or HC) with an overall accuracy of 78.50% and the rules obtained were:

1. *If SCI-ABS Domain 4 (Phobias), section B (Weight Gain Phobia) total score is ≥ 3), then the individual is classified as a EDs subject;*

2. *If SCI-ABS domain 9 (Impairment and Insight), section A (Impairment), item 5 is ≥ 1), then the individual is classified as a EDs subject;*

3. *If MOODS-SR, item 154 is ≥ 1 and MOODS-SR, item 24 is ≥ 1, then the individual is classified as a EDs subject;*

4. *If the previous three roles are not applicable, then the individual is classified as an HC subject.*

The reported set of decision rules shows high accuracy in classifying EDs individuals (44/53; accuracy=83%) and HC (40/54; accuracy=74%), AUC=0.77 and F1=0.79. The classification accuracies obtained by the main classifiers are shown in **Table 3**.

Table 3. The correct classification, with attributes selection, achieved by different classifiers measured by: accuracy, AUC, F1.

Classifier	**Accuracy (%)**	**AUC**	**F1**	**Correct Classification**	
Naïve Bayes	86.92%	0.88 (d=1.66)	0.87	EDs 48/53	HC 45/54
Logistic Regression	72.90%	0.77 (d=1.06)	0.73	EDs 37/53	HC 41/54
Simple Logistics	80.37%	0.87 (d=1.59)	0.80	EDs 42/53	HC 44/54
Support Vector Machine	81.31%	0.81 (d=1.24)	0.81	EDs 42/53	HC 45/54
Random Forest	85.98%	0.90 (d=1.81)	0.86	EDs 44/53	HC 48/54

3.1.3. The identification of the most important features identifying eating disorders

Given the large number of predictors (number of attributes = 347), with respect to the sample size (n=107) we selected the most important predictors. With this purpose, we run a supervised attribute selection procedure called *wrapper* (Kohavi & John, 1997), which identifies the subset of features for a given classifiers (here we used Naïve Bayes classifier). Along with age, the most important set of attributes identified by the system are shown in **Table 4**.

Table 4. The most important set of attributes identified by the application of a supervised attribute selection using a wrapper subset evaluation.

SCI-ABS domain	Section	Item
4 Phobias	B (Weight Gain Phobia)	*"Have you ever had extended periods of time when you… felt uncomfortable and guilty, even after eating small amounts of food such as chocolate, sweets, pasta or deep fried food, because you were afraid that you might gain weight?"*
4 Phobias	C (Secondary Social Phobia)	*"Have you ever had extended periods of time when you felt very badly or you avoided… going out for dinner because of your figure of the amount you eat?"*
5 Avoidant & compulsive behaviors	-	*"Have you ever had extended periods of time when you…carefully planned your day according to your food?"*
6 Weight maintenance	A (Dietary Habits)	*"Have you ever had extended period of time when you… took medication such as thyroid hormones in order to prevent weight gain?"*
SCI-ABS total score	-	-

As the last step, we run a Naïve Bayes classifier using as inputs the reported attributes which yielded an accuracy of 90.65% in classifying EDs patients (49 out of 53) from HC (48 out of 54) with AUC= 0.88 (d=1.66), F1= 0.91. As shown, the overall accuracy is very high indicating that the selected combinations of features capture the most important determinants in the discrimination of EDs individual vs HC.

4. Discussion

Clinical studies examining EDs suggest that the majority of individuals with AN or BN do not fully recover in short-term periods. From this perspective, EDs can be comparable to several other chronic conditions significantly associated with comorbid psychopathology, and severe medical diseases, negatively affecting subjective QoL. Although scientific research stressed the medical impairments that often result from EDs, research on the devastating psychological effects and QoL of these patients is proceeding slowly (Ágh et al., 2016; Wu et al., 2019). Nevertheless, recent epidemiological evidence demonstrates higher treatment requests from patients but lower detection of EDs from healthcare systems, high psychiatric comorbidities (around 70%) and great impairment of health related QoL (Keski-Rahkonen & Mustelin, 2016).

In this study, we utilized two instruments assessing the anorexic-bulimic spectrum and the comorbid sub-threshold mood spectrum in a lifetime perspective, with the aim to identify signs and symptoms that might characterize, during the entire lifespan, the phenotypic expression of anorexia and bulimia, considering also the psychological background characterized (especially in bulimic patients) by mood instability.

We compared patients with EDs and HC with a ML analysis that obtained accuracy higher than 70%. Based on all variables considered, the analysis revealed that SCI-ABS 'Phobias' domain (more in detail, 'Weight Gain Phobia' total score), the 'Impairment and Insight' item 5, ('…your relationship with food was all you could think about?') were the best psychological elements in discriminating EDs patients from HC (accuracy range: 72.90-86.92%). We found also that one item of the MOODS-SR, namely the item 154 ('you were less sexually active than is typical for you?') characterized patients with EDs.

The very high overall accuracy determined by the ML analysis was indicative that the selected combinations of features captured the most important determinants in the discrimination of EDs patients vs HC.

However, it is noteworthy that among the numerous sub-threshold dimensions assessed by MOODS-SR, only one item was able to discriminate between HC and EDs patients. This finding could be explained with the fact that EDs individuals were all examined in an outpatients setting, with mild severity levels of EDs, and an overall good level of adaptation. Conversely, the ABS items selected by the ML analysis confirmed how, even in a sample characterized by low levels of severity, the extreme polarization of ideas on weight and food control are the main cognitive assets of EDs patients.

Even if with all the limitations due to a retrospective design, we believe that this study confirmed the need of an accurate and systematic assessment of a wider number of EDs signs and symptoms than those described the DSM categories. In order to enhance the assessment of the peculiar and undetected features of EDs along with the reliability of spectrum disorder evaluation, in the present study we suggested the application of ML analysis to a dimensional spectrum assessment, in order to confirm its validity and replicability.

The method of the supervised ML, an area of artificial intelligence dedicated to the development of algorithms able to automatically extract clinical information from available datasets provided reliable information on the proposed model. Thus, ML methods used cross-validation in order to guarantee the generalizability of the results. In recent years, ML has been increasingly applied in different domains of medicine and psychology with an exponential growth in the publications describing its use and its potentials as a set of methods and procedure able to augment psychometric testing.

Giving that ML is more oriented to prediction rather than model fitting, an increasing use of such methods has been recently proposed (Yarkoni & Westfall, 2017; Yarkoni, 2019). ML is usually more accurate than traditional statistical methods in classification tasks.

We used different ML classifiers to assess which of the variables considered were the most informative in the classification of EDs patients versus HC and to evaluate the maximum classification accuracy that may be achieved.

Furthermore, we have shown that a reduced set of items might perform equally well as the full-scale indexing to the most relevant items that maximize discrimination among patients' groups (EDs vs HC). All the analysis reported here have been conducted using 10-fold cross-validation, a procedure that reduces overfitting and maximizes replicability of results. Using procedures that maximize replicability of results is particularly relevant considering the lack of replicability detected in psychology and medicine (Schooler, 2019), where scientific studies are difficult to replicate. Cross-validation, as used in all the analysis reported here, represents a useful approach in order to verify replicability (exact replication), estimating the effectiveness of the ML models. The feature items selection was effective in identifying the most informative items while, at the same time, not reducing the discrimination power of the applied tests.

5. Conclusions

Clinical questionnaires such as SCI-ABS or MOODS-SR evaluate the presence of a given number of symptoms disorders' related. The identification of an efficient and reliable subset of items not only is useful in deriving a classification procedure which has the highest accuracy possible, but also may help the clinician as a guideline during clinical interview.

The issues identified by the efficient subset of items could be usefully mapped during clinical interview in order to reach a valid clinically grounded evaluation, to communicate effectively scientific outcomes and to rely on outcomes provided by the clinical research (Coin et al., 2009; Orrù et al., 2009; Settineri & Femminò, 2019; Settineri & Merlo, 2019). In conclusion, the very high overall accuracy obtained is indicative that the selected combinations of features capture the most important determinants in the discrimination of EDs individuals vs HC.

Author Contributions

Conceptualization, G.O. and M.M. (second author); methodology, G.O.; software, G.O.; formal analysis, G.O.; investigation, G.O. and M.M. (second author); resources, L.P. and M.M. (forth author); data curation, G.O.; writing original draft preparation, G.O. and M.M. (second author); writing review and editing, G.O., M.M. (second author), C.C. and R.C.; visualization, G.O.;

supervision, G.O., M.M. (second author) and A.G. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest Statement

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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