Multidimensional Assessment of Student Mental Health during the COVID-19 Pandemic: A Latent Profile Analysis Integrating Positive Psychology

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Background: The mental health of young adults, especially university students, has become an increasingly concerning issue. In order to develop targeted interventions and support initiatives, it is essential to comprehend distinct mental health profiles and identify vulnerable groups among Tunisian university students. This study aimed to achieve three main objectives: (a) to empirically identify different profiles of mental health among young adults in Tunisia, based on a person-centred approach using the dual-factor model of mental health, (b) to outline the identified profiles, which incorporate both psychopathological symptoms and indicators of positive subjective well-being, across sociodemographic and academic achievement factors, and (c) to establish predictors of these profiles.

Methods: Cross-sectional data was collected from a cohort of teenage Tunisian university students (n = 1185, 54% females), aged between 18 to 24 years old (Mean = 21.10; SD = 2.02). Participants completed an online survey, which included assessments of socio-demographic characteristics, academic achievement, stress, depression, anxiety, spiritual well-being, life satisfaction, and happiness.

Results: Analysis of latent profiles revealed the existence of three distinct mental health classes. The first profile (21.1%) represented individuals with poor mental health. The second profile (42.5%) consisted of individuals with moderate mental health, and the third profile (36.4%) comprised individuals with good mental health. Significant differences were found between these three classes regarding family income and academic completion (p<0.01 and p<0.001, respectively). Multinomial logistic regression analysis provided Odds Ratios (OR) with Confidence Intervals (CI), revealing that the poor mental health class was associated with low family income (OR: 3.28; 95% CI: 1.90–5.63) and failed academic achievement (OR: 46; 68% CI: 28.23–77.20). Additionally, the moderate mental health class was linked to low family income (OR: 1.88; 95% CI: 1.30–2.72), living with family (OR: 0.70; 95% CI: 0.49–0.99), and failed academic achievement (OR: 1.50; 95% CI: 1.06–2.11). However, no significant associations were found for middle family income (OR: 1.27; 95% CI: 0.93–1.74) and dwelling in university residence (OR: 0.81; 95% CI: 0.60–1.10) as predictors.

Conclusion: This study revealed that a considerable number of university students aged 18 to 24 were vulnerable to mental health issues, irrespective of gender and age. However, students belonging to classes with low incomes and those who did not pass exams were identified as the most vulnerable groups. It is crucial to pay particular attention to these students and provide appropriate support and interventions.

Keywords: Academic Achievement, Mental health, Person Centred-Approach, Positive Psychology, Profiling

INTRODUCTION

Since the Coronavirus Severe Acute Respiratory Syndrome (SARS-CoV-2) pandemic has affected humans' lifestyles and behaviours, public mental health profiles are changing at breakneck speed all around the world (1). Currently, a wide range study highlighted emerging new psychiatric symptoms, an increase in mental disorders and widespread deterioration of mental health related to the Coronavirus Disease 2019 (COVID-19) pandemic (2) In this regard, some meta-analysis and systematic reviews have reported a high-level prevalence of depression, anxiety, insomnia, and psychological distress (3). In fact, from the onset of the pandemic, several reasons justified the concerns of researchers and the practical's mental health care services in several countries. Stress and worry were directly related to the previously unknown of the virus and its spread nature, the uncertainty and the less knowledge of this disease (4). Second, security measures to combat the spread of the virus has required mandatory confinement, social distancing and general lockdowns (3). In point of fact, many studies in different countries have reported changes in adult's life styles behaviours and several mental health disorders that have been directly linked to lockdowns and imposed social distancing for young adults, adolescents (5, 6) and children (1). Disinformation and conspiracy theories about the virus and vaccines that have taken over social media networks (7) declines well-being mental health over the world. In fact, health disinformation is considered as global public health threat. For this, several research papers suggest applying psychological approaches in the pandemic and post-pandemic era (8). In this perspective, numerous studies about COVID-19 have focused on mental health problems (9). However, before the pandemic appearance, for a while, research claimed the integration of positive psychology. In this point of view, mental health is proposed as a two-factor model that involves both low levels of psychopathology and high levels of well-being (10). Indeed, several research (11) stipules that entire mental health involves psychopathological symptoms (negative mental health) and subjective well-being (positive mental health). In that way, a lot of researchers and clinicians are realising that a good psychological state is specified not only by the absence of mental disorders, but also by the appearance of good mental health indicators (12). As a matter of fact, according to a definition, the World Health Organisation defines mental health as "a state of well-being that allows a person to participate and contribute to society and to cope with life situations and the stress they generate" (13). More specifically, mental health is a dynamic state of internal balance which enables individuals to use their skills in accordance with the fundamental values of society, basic cognitive and social skills; the ability to identify, communicate and modulate own feelings (14). To facilitate comprehension, decision-making and psychiatric intervention on this dynamic state, a lot of studies have been carried out. A part of these investigations allows to identify, model and classify groups in several populations according to their mental health states. In this area, the person-centred approach was widely used to identify different profiles that are configured by similar mental health patterns. In sooth, it builds typologies based on observed variables and assumes homogeneous clusters identification in communities, as an example, the most vulnerable groups. During the COVID-19 pandemic, two mixtures modelling techniques were expansively used to segment groups based on several psychological constructs of mental health. The first is latent class analysis (LCA) which deals with qualitative variables, and the second is the Latent Profile Analysis (LPA) which deals with continues variables.

Latent profile analysis (LPA) is a flexible procedure that supports probabilistic identification of mental health subgroups. Using this technique, several mental health clusters were identified for general populations in different countries based on psychopathological symptoms (for example, stress, anxiety and depression). Nevertheless, little research has classified cohort individuals based on positive and negative mental health constructs. Furthermore, these studies have not given importance to student's cohorts.

Therefore, the objectives of this study were to (a) empirically identify, from dual-factor model of mental health, different profiles among a cohort of sudents in Tunisia based on person-centered approach, (b) outline identified profiles (created with both psychopathological symptoms and indicators of positive subjective well-being), across the sociodemographic and the academic achievement, and (c) establish predictors of these profiles.

MATERIALS AND METHOD

Data Collection and Procedures

Cross-sectional data was collected from the second of July until the end of the month, after the academic year

concluded. By the end of the data collection period, Tunisia had reported a total of 29,423 deaths and 1,153,361 cases of COVID-19 as of July 31, 2021, and the nationwide lockdown was lifted (15). To gather survey participants, we utilized the "Google Forms" application and circulated the invitation through major social media groups. The snowball sampling method was employed, where participants who agreed to take part in the study were asked to invite other participants from their Facebook friends list. The phases of data collection are illustrated in Figure 1.
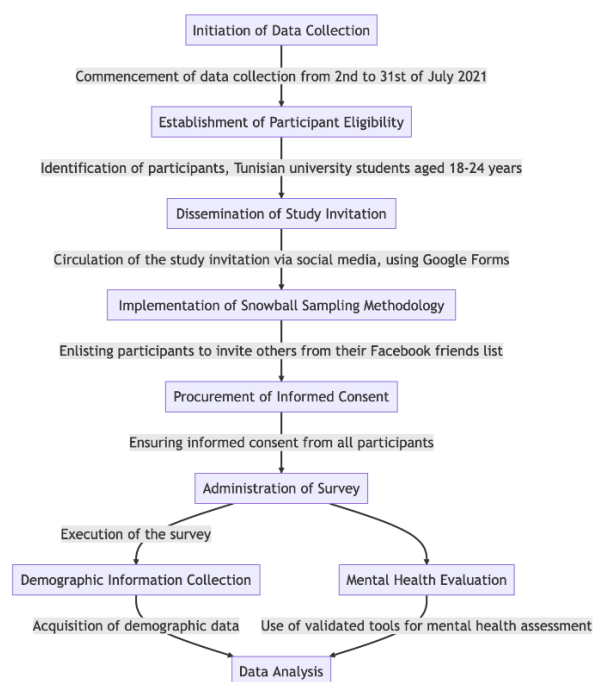

Figure 1. Flowchart of data collection

The "Google Forms" platform proves to be a valuable web-based tool, offering a wide range of options for creating surveys. It prioritizes user privacy and maintains strict confidentiality policies, ensuring that all recorded information remains anonymous and non-identifiable. Further details about this platform can be found at: Google Forms: Free Online Form Creator | Google Workspace.

Eligibility for participation in this study is limited to Tunisian students between the ages of 18 and 24, enrolled in a Tunisian university. However, individuals with a positive COVID-19 test at the time of the survey were excluded from the study.

As of January 2021, there were approximately 8,270,000 Facebook users in Tunisia, making up around 67.4% of the total population (16). Based on this population size, a minimum sample of 386 participants was determined using the following formula:

$$n = (Z^2 * p * q * N) / [(Z^2 * p * q) + ((N - 1) * E^2)]$$

Z = 1.96 (95% of confidence level)
p = q = 0.5 (to assume maximum variability)
E = 5% margin of error
N = population size

Measures
Demographic characteristics
The study collected data on various demographic characteristics such as age, gender, academic achievement (including success and failure in the previous year of study), and family income, which was categorized as follows: minimum wage, between two and three times the minimum wage, and more than three times the minimum wage.

Regarding mental health measures, the study utilized previously validated instruments available in the participants' language, widely used in mental health research during the pandemic

The Depression Anxiety Stress Scale-21(DASS-21)
To measure stress, anxiety and depression, a validated Arabic version with robust psychometric properties of DASS-21 was used (17). The DASS-21 has 21 items in three subscales of seven items each. They ask about depressive symptoms (for example, feeling depressed and blue), symptoms of anxiety (for example, feeling close to panic), and general symptoms of stress (for example, tending to overreact excessively in situations). The answer options are on a four-point Likert scale (0 = did not apply to me at all, and 3 = applied to me most of the time). Higher scores indicate more psychological distress.

The reliability alpha coefficient was good for overall scale (0.88). While the alpha internal consistency of the subscales was 0.67, 0.76, and 0.81 for stress, anxiety and depression respectively.

Arabic Scale of Happiness (AHS)
Each item on the AHS is answered on a 5-point Likert-type scale, with scores ranging from 1: Not at all, and 5: Very high. The total score can vary from 15 to 75, with higher scores indicating greater happiness (18).

The Arab 15-items Happiness Scale was administered to measure Happiness. Each item is answered on a five-point Likert-type scale from 1 (not at all) to 5: very high. A score of 15 to 75 forms an index of happiness. For internal consistency, measured using Cronbach's alpha and test-retest reliability, which is greater than 0.80 indicates good internal consistency and high temporal stability.

The Spiritual Well-Being Scale (SWBS)

To measure spiritual well-being, we used an Arabic version of the SWBS (Paloutzian et al., 2021). The SWBS is made up of two factors: religious well-being (RWB) and existential well-being (EWB), which are assessed on a 6-point Likert scale ranging from 1 "strongly agree" to 6 "strongly disagree". Total SWBS scores range from 20 to 120, while the scale demonstrated adequate internal consistency (alpha = 0.83 and alpha = 0.82 for RWB and EWB respectively ([2]).

Satisfaction With Life Scale (SWLS)

The SWLS is a five-item scale used as an overall rating of life satisfaction. Items are scored on a seven-point Likert-type scale that ranges from 1 (strongly disagree) to 7 (strongly agree). An example item is: "In most cases my life is close to my ideal." Higher scores reflect higher levels of life satisfaction. In this study, the SWLS had high internal consistency with a Cronbach's alpha value of 0.88. The scale showed good evidence of reliability and validity in the Arabic language ([19]).

Statistical Analysis

All data analyses were performed using R software (version 4.0.2) and RStudio (version 1.3.1093) for Windows, and Statistical Package for the Social Sciences" software (IBM SPSS software for Windows, version 26.0, IBM Corp., Armonk, NY, USA; published 2019).

Before proceeding with the analysis of the LPA, we inspected the normality of the distributions and the internal consistency of the scales (in Tunisia) by the coefficients of Skewness and Kurtosis and the classical Cronbach's alpha coefficients respectively. To identify the unobserved underlying group structure in the data, i.e., the underlying latent structure, based on positive and negative mental health factors we applied LPA.

For LPA, we used the Tidy LPA package which allows to test four different models on several classes. Model (1) is defined with equal variances and zero profile covariances. The profile indicators of the model (2) are defined by variance variables and zero profile covariances. The profile indicators of the model (3) are defined with equal profile variances and equal profile covariances. The profile indicators of the model (6) are determined with variable profile variances and variable profile covariances. To determine the optimal model and the number of profiles, we consider a multitude of fit indices: the lowest values of "Bayesian Information Criterion (BIC)" and "Akaike Information Criterion (AIC)", the p-value of the bootstrap test of the likelihood ratio (BLRT) and entropy (values greater than 0.64 are acceptable).

In addition, an average posterior probability of > 0.7 suggests a robust and valid classification. Each participant was assigned to the latent profile with the highest membership probability. The optimal model was selected based on the theoretical support and the conceptual interpretability of the profiles at the same time.

We realised a multivariate analysis of covariance (MANCOVA) to test the hypothesis that mental health would differ based on class membership among the students, after controlling for age. Subsequently, analysis of the covariance (age = Covariate) and Sidak's Post-Hoc tests were used to compare the mean values of the scores for the different measurement scales. While comparisons between categorical socio-demographic variables were made by chi-square tests. The partial-squared Eta and Cramer's V effect sizes were calculated for the continuous and categorical variables respectively.

Finally, multinomial logistic regression analysis (with age as Covariate) was performed with the variables gender, family income, dwelling, and academic achievement to determine which variables significantly affected the mental health outcomes. We used the standard error (SE) to compute confidence intervals and evaluate the statistical significance. Additionally, we utilized employed the adjusted odds ratio (OR) to assess the relationship between independent variables and the outcome classes.

RESULTS

The final sample included 1,185 students. The participants are aged from 18 to 24 years old (Mean = 21.10; SD = 2.02), of which the majority were women (54%). For the family income variable, (31.5%) of the participants come from low-income families, (42.3%) come from families with average incomes and (27.2%) come from families who have good incomes.

In terms of dwelling during the academic year, (21.4%) of students reside with their families, (42.1%) live in university residence and (36.5%) were renters of houses. The majority of students passed (66.1%), while (33.9%) of students failed in their previous academic year. The participants who tested positive for COVID-19 at the time of the survey were excluded (n = 27).

Normality and Internal Consistency of Scales

Regarding the normality of the distributions, the scores for all items of the measurement scales had normal distributions with acceptable values of skewness and kurtosis. The internal consistency indices for the different study scales were all adequate in our context. Indeed, Cronbach's alpha coefficients were 0.87, 0.81,

0.82 for stress, depression and anxiety respectively. For the Spiritual Well-Being Scale, the alpha values were 0.87 and 0.84 respectively. While for the SWLS and ASH scales, the coefficients were good with respective values of 0.91 and 0.83.

In the next step, all scores of scales factors (stress, depression anxiety, RWB, EWB, SWLS and ASH) were included in a set of successive LPA models.

Deciding on the Number of Profiles

We investigated the fit statistics for solutions with two to four profiles in each model (Table 1). According to LPA, the solution with three latent profiles of varying variance and covariance was identified as the best-fit and most interpretable model (best BIC = 10873.30), with inadequate certainty of classification (entropy = .73). The probability of the selected class varies between minimal probability Prob-min =0.85) and maximal probability (Prob_max= 0.95).

Table 1. Latent Class Analyses: Model Fit and Usefulness Indices.

Model#	Classes	AIC	BIC	Entropy	Prob_min	Prob_max	BLRT_p
1	2	14633.54	14745.24	0.89	0.97	0.97	0.01
1	3	13024.17	13176.49	0.91	0.96	0.96	0.01
1	4	12510.39	12703.34	0.88	0.87	0.95	0.01
2	2	14552.96	14700.21	0.89	0.97	0.97	0.01
2	3	12654.17	12877.58	0.93	0.96	0.97	0.01
2	4	12070.18	12369.76	0.91	0.93	0.97	0.01
3	2	11299.57	11517.90	0.72	0.90	0.92	0.01
3	3	11157.24	11416.19	0.79	0.90	0.91	0.01
3	4	11057.02	11356.60	0.77	0.81	0.94	0.01
6	2	10858.10	11218.61	0.89	0.95	0.97	0.01
6	3	10330.00	10873.30	0.73	0.85	0.95	0.01
6	4	10172.63	10898.72	0.75	0.77	0.96	0.01

Footnote: AIC=Akaike Information Criterion, BIC=Bayesian Information Criterion, Prob_min= minimal probability, Prob_max = maximal probability, BLRT_p= p-value of the bootstrap test of the likelihood ratio, # model 4 and model 5=not avaible in algorithm

The three profiles exhibited distinct quantitative characteristics: individuals with a high probability (Table 2). MANCOVA analysis results suggests that mental health in classes differs significantly (Wilks' Lambda =0.41; F (14, 2350) = 95.86*** (Eta =0.36).

Also, univariate Ancona showed that the three profiles, significantly discriminated study cohort in stress (p <0.001, Eta = 0.37), depression (p <0.001, Eta = 0.41), and anxiety (p <0.001, Eta = 0.24). Also differences in the three clusters on positive mental health have been highlighted: RWB (p <0.001, Eta = 0.40), EWB (p <0.001, Eta = 0.41), SWLS (p <0.001, Eta = 0.45) and ASH (p <0.001, Eta = 0.45). Sidak post-hoc tests confirmed the differences between the three classes (class1vs class2; class1vsclass3; and class2vsclass3).

The first class includes 56% female and 44% male. 53.6% have low family incomes, 27.6% have median family incomes and 18.8% have high family incomes. The distribution Dwelling in this class were 18.4%, 46.4% and 35.2% for living with a family, living in a university residence and living in a rental house respectively. This cluster is made up of 90.4% who succeed their university year and 9.4% who failed.

The second class is formed by individuals of females (55.6%) and males (44.4%). For this cluster, family income was divided into low income (29.6%), average income (44.2%), and high family income (26.2%). The distribution of the dwelling of this second cluster was: accommodation with the family (21.2%), accommodation in a university residence (40.7%) and accommodation in a rental house (38.1%). This group is made up of 22% of students who failed the previous academic year and 78% who passed university exams.

The third class is made up of 51% women and 49% men. Individuals adhering to this profile are divided into low family income (20.9%), average family income (45.7%) and high family income (33.4%). Thus, 23.4% of this cluster live with their families, 41.3% live in a university residence and 35.3% live in a rental house respectively. This cluster is made up of 90.4% who spent their university year and 9.4% who failed.

Contingency tables on the various socio-demographic parameters and academic success were calculated (Table 2). The results did not show any significant differences for gender (Chi2 = 2.41; Cramer's V = 0.04) and dwelling (Chi2 = 3.94; Cramer's V = 0.4). While very significant differences were demonstrated for the variable income (Chi2 = 82.05; Cramer's V = 0.19) and academic achievement (Chi2 = 455.84; Cramer's V = 0.53).

Table 2. Demographics, academic achievement, and differences in mental health scales for the three profiles

	Profile 1	Profile 2	Profile 3	X2/F	Partial eta squared/Cramer's V	Post hoc test
Profile	250 (21.1)	504 (42.5)	431 (36.4)			
Age	21.25 ± 2.12	21.10 ± 1.98	21.02 ± 2.02			
Gender				2.41	0.04	
Female	140 (56.0)	280 (55.6)	220 (51.0)			
Male	110 (44.0)	224 (44.4)	211 (49.0)			
Family income				82.05**	0.19	
Poor	134 (53.6)	149 (29.6)	90 (20.9)			
Middle	69 (27.6)	223 (44.2)	197 (45.7)			
High	47 (18.8)	132 (26.2)	144 (33.4)			
Dwelling				3.94	0.4	
With family	46 (18.4)	107 (21.2)	101 (23.4)			
Student housing	116 (46.4)	205 (40.7)	178 (41.3)			
Rented house	88 (35.2)	192 (38.1)	152 (35.3)			
Academic achievement				455.84***	0.53	
Failed	226 (90.4)	111 (22.0)	65 (15.1)			
Succeded	24 (9.6)	393 (78.0)	366 (84.9)			
Stress	2.43 ± 0.46	1.90 ± 0.51	1.52 ± 0.51	341.64***	0.37	3<2<1
Depression	1.86 ± 0.38	1.43 ± 0.45	1.17 ± 0.47	264.3**	0.41	3<2<1
Anxiety	1.61 ± 0.37	2.54 ± 0.71	2.96 ± 0.56	189.44***	0.24	3<2<1
RWB	1.55 ± 0.38	2.52 ± 0.72	2.93 ± 0.61	404.8***	0.41	3>2>1
EWB	1.47 ± 0.24	2.85 ± 0.89	3.22 ± 0.70	390.76***	0.40	3>2>1
SWLS	1.45 ± 0.22	2.41 ± 0.66	2.96 ± 0.69	477.13***	0.45	3>2>1
ASH	3.32 ± 0.29	2.62 ± 0.61	2.10 ± 0.69	488.90***	0.45	3>2>1

Data in table are presented as Mean ± SD or No. (%)

Note. Overall MANCOVA: Wilks' Lambda =0.41; $F_{(14, 2350)}$ = 95.86*** (**Eta** =0.36). ***: $p<0.001$.

The first profile (21.1%) presents vulnerable or problematic clusters in terms of mental health with negative characteristics. The second profile (42.5%) presents clusters with moderate mental health. In addition, the third profile (36.4) presents people in good mental health.

Table 3. Multinomial logistic regression for profiles

Predictors	SE	Wald(df)	Signification	OR	95% Confidence Interval for OR	
					Lower Bound	Upper Bound
Profile 1						
Age [a]	0.05	0.00	0.993	1.00	0.90	1.10
[Gender [b] =Female]	0.20	0.10	0.757	1.07	0.71	1.59
[Family income [c] = Low]	0.28	18.41	0.000	3.28***	1.90	5.63
[Family income = Middle]	0.27	0.03	0.865	1.05	0.62	1.78
[Dwelling [d] =With family]	0.28	1.68	0.195	0.70	0.40	1.20
[Dwelling = university residence]	0.24	2.52	0.112	0.68	0.43	1.09
[Academic achievement [e] =Failed]	0.26	224.18	0.000	46.68***	28.23	77.20
Profile 2						
Age	0.03	0.01	0.928	1.00	0.94	1.07
[Gender= Female]	0.13	1.38	0.241	1.17	0.90	1.52
[Family income =Low]	0.19	11.10	0.001	1.88**	1.30	2.72
[Family income =Middle]	0.16	2.30	0.129	1.27	0.93	1.74
[Dwelling =With family]	0.18	4.05	0.044	0.70*	0.49	0.99
[Dwelling = university residence]	0.16	1.76	0.184	0.81	0.60	1.10
[Academic achievement=Failed]	0.17	5.32	0.021	1.50*	1.06	2.11

Footnote:SE= standard Error, Wald= Wald test, df= Degrees of freedom, OR= Adjusted Odds Ratio,£ Profile 3 =reference; AOR= Adjusted Odds Ratio; a: age =Covariate; b: male=reference; c: High family income=reference; d: familial dwelling = reference; e Failed=reference. * $p<0.05$; ** $p<0.01$; *** $p<0.001$.

Multinomial Logistic Regression

Multinomial logistic regression models were run modeling the probability of predicting class memberships. Table 3 summarizes the corresponding computed standard error (SE), Wald test and adjusted odds ratio (OR) with their 95% confidence intervals. Results of multinomial logistic regression analysis indicated that poor mental health class were related to low family income (OR: 3.28; 95% CI: 1.90–5.63) and failed academic achievement (OR: 46; 68% CI: 28.23–77.20). However, middle family income (OR: 1.05; 95% CI: 0.62–1.78), dwelling with family (OR: 0.70; % CI: 0.40–1.20), dwelling in university residence (OR: 0.68; 95% CI: 0.43–1.09) could not predict membership in this class.

In addition, moderate mental health class were associated to low family income (OR: 1.88; 95% CI: 1.30–

2.72)., dwelling with family (OR: 0.70; 95% CI: 0.49–0.99) and failed academic achievement (OR: 1.50; 95% CI: 1.06–2.11). Moreover, no significant values were found for middle family income (OR: 1.27; 95% CI: 0.93–1.74)., dwelling in university residence (OR: 0.81; 95% CI: 0.60–1.10) as predictors. Finally, age as covariate was not a predictor of belonging to poor (OR: 1; 95% CI: 0.90–1.10) and moderate (OR: 1; 95% CI: 0.94–1.07) mental health classes.

DISCUSSION

The results of the present study validated a three-profile model that showed significant differences in both negative and positive mental health selected concerns. Indeed, the three profiles exhibited significant differences in stress, depression and anxiety. The good mental health cluster is made up of 36.4% particpiants. Nevertheless, the two poor and moderate mental health classes displayed the majority of cases with 21.1% and 42.5% respectively. In addition, significant differences were highlighted for the three positive mental health constructs: spiritual well-being, satisfaction with life and Happiness.

Among the main results, no difference of gender, nor of dwelling for the classes' membership was highlighted. However, for the family income and school success, significant variations have been revealed.

Results of multinomial logistic regression analysis indicated that poor mental health class were related to low family income and failed academic achievement. However, middle family income dwelling with family dwelling in university residence could not predict membership in this class. In addition, moderate mental health class was associated to low family income, dwelling with family and failed academic achievement.

Similar results to our study have been reported on Turkish university students (20). The LPA model retained three classes of psychological symptoms (high, medium and moderate). The positive and negative mental health factors (fear, depression, anxiety, stress, resilience and mindfulness) were useful to discriminate classes. However, this research suggested, that female gender was positively related to negative mental health. In addition, psychosocial factors such as life satisfaction and social support were positively associated with mindfulness and resilience, and were negatively associated with fear, depression, anxiety and stress related to COVID-19. Furthermore, Browning et al. (21) reported a three psychological profiles model on a large student's sample aged between 18 and 24 years in USA. The LPA carried out, displayed a solution with high,

moderate and low-level classes based on mental health constructs (21). The study also identified associations between family income and the vulnerable class in terms of mental health. In contrast to our results, associations between mental profiles and gender variables were found.

Our results were also in line with the results of Zhen and Zhou (22) which investigated co-occurring patterns of post-traumatic stress disorder, depressive symptoms, and post-traumatic growth among Chinese adolescents (22). The results showed three latent profiles characterized by psychopathological symptoms.

In another parallel study, Liu et al. (23) identified, through LCA techniques, three distinct subgroups on mental health: with good, mild and weak symptoms. The results also showed that gender and level of education accentuated the depression and anxiety in the poor mental health and the mild mental health groups (23). In line with our contribution about subjective well-being, Özmen et al. (24) in a study conducted among Turkish aged 18 years old and over, showed a relationship between fear of COVID-19, well-being and perceived life satisfaction. Moreover, compared to the pre-pandemic situation, Coppola et al. (25) found a positive association between the COVID-19 pandemic and psychological distress, as well a negative correlation between COVID-19 pandemic and spiritual well-being. In contrast to our pandemic study, results showed that women perceive higher levels of spiritual well-being than men. In addition, age affects positive mental health aspects such as spiritual well-being.

Likewise, the present results are not consistent in results related to gender with those obtained on a British cohort (26). This investigation which used mixed latent class models and regression with fixed effects identify the gender as a predictor of change in mental health. Women were more likely than men to have mental health declines. Differences in results for the gender variable may be due to contextual differences related to culture.

For the results relating to family income, our results were in line with many studies that have shown that family income can influence mental health states (27).

In another perspective, Harju et al. (28) studied the well-being in the UK and France with cross-sectional data during the lockdown. The model which used psychosocial factors as an input's parameters revealed five distinct profiles: Moderately positive, languishing, flourishing, mixed feelings, and indifferent. Besides, mixed feelings, and indifferent clusters did less than 10% of the cohort of study.

Generally, we looked that mental health status of the majority adolescents and young adults decline in COVID-19 pandemic. In fact, these declines can be explained by several factors, including social isolation, economic recession, school and university closings, lack of outdoor activity, variation in eating habits and aberrant sleep (29). The Coronavirus crisis has caused serious damage to social life; indeed, the recommendations of social distancing have put social practices in crisis (5). Adolescents and young adults have lost touch not only with their peers, but also with their extended communities of protective adults (e.g., teachers) who may notice signs of abuse and distress (30). Therefore, feeling socially disconnected during the pandemic was associated with higher levels of anxiety and depressive symptoms and lower levels of life satisfaction (31). On the other hand, a little research suggests that the confinement reinforced cravings and solidarity both within the family and among students in the classroom (32).

From a different angle, adolescence is a time of confusion, crisis and turmoil that presents a laborious, and conflictual transition from childhood to adulthood (33). This age range is also a time of transition with unique known risks for the development of mental health problems. Although, most young people become healthy in adulthood, this phase makes them very vulnerable to mental health problems. Several mental illnesses, including depression, anxiety (34) with a risk of persisting throughout adult life, creating long term morbidity and considerable burden on society.

From another perspective, several studies have established a strong link between mental health and student academic success. Indeed, the current results are consistent with those found following a longitudinal study carried out by Davies et al. (35), who reported a negative association of depressive symptoms with later school results (35). Also, in another study on children, Sellers et al. (36), found that mental health problems are strongly associated with negative educational outcomes in recent generations. Additionally, academic performance, and in particular grades, has been shown to influence future employment, health, and social functioning worldwide (37). The relationship between depressive symptoms and academic achievement in adolescence has received considerable attention.

We can therefore suggest a negative association of depressive symptoms with later school results. However, this association remains poorly understood, with a substantial uncertainty around its directionality, its change over time, and the coexistence of anxiety and/or externalizing symptoms.

Limitations of the Study

This research has certain limitations. Certain psychological, biological, interpersonal and social determinants involved in young adults' mental health has not been considered. We relied solely on data obtained from online responses. It may be preferable to use other tools such as observing the behavior of the individual in natural environments (universities).

Our LPA results are specific to this period and cannot necessarily be generalized to other contexts. Therefore, future research should consider measurement invariance in LPA (MI-LPA) to assess whether the number and nature of latent profiles are stable over time. (38, 39)

CONCLUSIONS

This study has highlighted the existence of three distinct mental health profiles - good, moderate, and poor, during the ongoing pandemic, each exhibiting unique characteristics and differences in the prevalence of stress, depression, anxiety, spiritual well-being, satisfaction with life, and happiness. While no significant differences were observed for class membership based on gender or dwelling, distinct variations were identified in relation to family income and academic achievement. The finding that low family income and failed academic achievement are linked to poor mental health underlines the influence of socio-economic factors on mental health outcomes. This connection is particularly noteworthy in the context of educational institutions, where these findings suggest a need for more integrated and holistic support systems that go beyond academic assistance to encompass mental health services and socio-economic support programs. Our study also underscores the heightened vulnerability of adolescents and young adults during crises such as the ongoing pandemic. This period of life, marked by significant transitions and uncertainties, can potentially trigger the onset of mental health issues, thereby making this age group particularly susceptible. The observed decline in the mental health status of this demographic during the pandemic calls for dedicated mental health interventions that are tailored to their specific needs and vulnerabilities. Moreover, the increased levels of anxiety and depression, along with reduced life satisfaction during the pandemic, highlight the adverse impacts of such crises on mental health and well-being. These findings emphasize the importance of strategies that promote social connectivity and provide comprehensive mental health support during periods of crisis. Taking these findings into account, our study offers crucial

guidance for a broad range of stakeholders, including social workers, psychologists, and policymakers. By illustrating the varying needs of the different mental health profiles, our study points towards the need for targeted, evidence-based decisions regarding interventions. These could be particularly beneficial for children, adolescents, and young adults who are susceptible to the mental health impacts of the COVID-19 pandemic. The findings also underscore the importance of adopting a comprehensive view of student mental health, one that considers the psychological, mental, and emotional dimensions along with academic performance. Such a holistic approach is essential for addressing and supporting the diverse mental health needs of students during challenging times such as these. Despite the substantial insights provided by this study, it invites further exploration, especially given the absence of significant gender differences in our findings, a contrast to previous research. Continued investigation into how gender and cultural variations influence mental health outcomes during crises will help in refining our understanding and strategies, ensuring they are effective and appropriate for all demographics.

ETHICS APPROVAL AND CONSENT TO PARTICIPATE

The participants in this current study handed their informed consent before the start of the survey. The protocol for this study has received ethical approval from the the Higher Institute of Sport and Physical Education of Kef, Kef (Tunisia). Moreover, the study was approved by the local Research Ethics Committee (22/2021).

CONSENT FOR PUBLICATION

Not applicable

AVAILABILITY OF DATA AND MATERIALS

The data related to this study is available from the corresponding author within reasonable request.

COMPETING INTERESTS

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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AUTHORS' CONTRIBUTIONS

N.G, I.D and M.R: conception and design.

N.G, MBA, I.D and N.B.L analysis and interpretation of the data.

M.R, M.S, N.C and FA: drafting of the paper.

N.G, I.D and N.L.B: revising it critically for intellectual content.

All authors gave their final approval to the version that will be published.

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DECLARATION

In accordance with the guidelines of the N Asian J Med [39], we disclose the use of AI assistance during the writing process of this manuscript. ChatGPT, an AI language model developed by OpenAI, was employed to enhance the academic English and improve the clarity and coherence of certain sentences in the discussion and conclusion section [40]. The primary objective of utilizing AI assistance was to ensure a high standard of language proficiency in the manuscript.

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