Report on Depression Risk Indicators Via Active Music Listening For Before and During COVID-19 Pandemic

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1. Introduction

The COVID-19 pandemic has had an ever-lasting impact on interpersonal relationships. People have resorted to different ways to cope with the pandemic; one being consumption of music. Individual well-being, moods and emotions go hand in hand with music[1]. Various studies have shown association between the psychological well-being of listeners and musical preference and listening strategies[2-3]. Increased emotional dependency on music during periods of depression has been reported[4]. The pandemic gives us an unprecedented opportunity to understand the relationship between mental well-being and time-varying music consumption using static and emotion-related features[5] from music listening history. With our work, we aim to unravel static patterns of depression in naturally occurring music listening behavior. Static and emotion-related features of 485 Last.fm users extracted from their listening histories, correlated with their mental well-being scores and musical engagement measures reveal that overall, users preferred music associated with happy and tender emotions during the pandemic. Users at risk of depression heavily relied on music associated with happy, sad and tender emotions, with reduced consumption of high arousal-low valence music associated with anger. We have observed that there was an increase in consumption of happy and calming music for both no-risk and at-risk users which illustrates the fact that most users experienced stress throughout the pandemic, and to distract their minds from the negative, they listened to more peaceful and joyful music. It is vital not only to identify individuals with depressive tendencies but also to design music recommendations by unraveling the music listening habits of such individuals.

2. Methodology and Experiments Performed

Overall Methodology can be divided into two steps :

1. Dataset Extraction/Collection
2. Feature Extraction and Statistical Testing

2.1. Dataset Extraction/Collection

Dataset comprises Last.fm Users' active music listening before and during the COVID-19 pandemic. The dataset consists of a 6 months listening history of 541 users before pandemic between 1st of Jan to 30th of June 2019. Similarly, we had 485 user's 6 months data between 1st of April 2020 to 30th of September 2020 containing a minimum of 5 sessions of music listening history during COVID-19. So, we considered the 485 users for our analysis for which we had listening history for both before and during COVID-19 adequately. This contains music listening history as well as top 500 tags associated with the songs listened by users in this period. These tags helped us in analyzing the emotions associated while listening to the songs. All these dataset is collected and analyzed anonymously and with following all the standards at IIIT Hyderabad.

We also had the Kessler's Psychological Distress Scale (K-10) scores of users, K-10 is a standard diagnostic questionnaire, used to assess users' well-being. This K-10 score helps us to determine while a user is at risk for depression i.e. showing symptoms related to depression. Also, these scores help us to determine the no risk users which don't have any symptoms related to depression. Each question is graded on a scale of one to five (none of the time to all of the time). The 10 item scores are then added together, so K-10 gives a numerical value ranging between 10 to 50. Low ratings imply minimal psychological distress, while high values indicate severe psychological distress.The set of cut-off scores that are used in the analysis to screen for psychological distress are as follows:

- 10-20 means users are considered as “No Risk” users in analysis.
- 20-29 means there are moderate chances of stress disorder.
- Above 29 means users are at high risk of depression and considered as “At Risk” users

By Considering the above scores, a total of 180 users are No Risk users, 120 are in At-Risk and remaining are at moderate or cannot say definitely cases.

2.2. Feature Extraction and Statistical Testing

2.2.1. Acoustic Features Analysis

The process for feature extraction for acoustic features can be divided into three parts: static, session-based, and dynamic feature extraction. Firstly, we have extracted 10 acoustic features from a track using Spotify's[6] public API and Spotipy package[7]. Spotify provides a wide collection of songs with their acoustic feature scores that can be used openly for research purposes. We have focused on danceability, loudness, speechiness, acousticness, instrumentalness, liveness, tempo, and mode as eight acoustic music qualities. Also, we extracted scores for Valence and Arousal (energy), which are emotional aspects of music and help us to map the music to VA space. VA space divides music pieces in 4 quadrants i.e. happiness (Q1), anger (Q2), sadness (Q3), and tenderness (Q4). Using this we have calculated a Quadrant Prevalence Score (QPS), which measures the proportion of tracks in each user's listening history that fall into each quadrant.

Next, we started session based feature extraction, in which we defined a session as a period of continuous listening activity that aids in acquiring time-varying values for audio and QPS attributes for each user. This continuous duration is taken by calculating songs within 2 hours. In case there was a break of more than 2 hours in listening history, we considered it to be a new session.

As discussed in the original paper[8], individuals at risk for depression may participate in repetitive music listening activities. Reason being at-risk users do not change easily or we can say more stubborn in terms of their listening habits. To capture this repetitiveness we calculate a Repetitiveness Index for each user. We have also calculated dynamics features to help us better comprehend consumers' mood fluctuations, which are characterized by variability and inertia. Illness and melancholy moods are associated with higher inertia and extreme variability.

2.2.2. Emotion Features Analysis

We performed analysis on tags based data. We used top 500 tags based on data extracted from Last.fm listening history of users per song. Firstly, we performed tag filtering using lower-casing, removing punctuation and stop-words, spell-checking, and checking for the presence of tag words in the English corpus. Then we retained tags that are most frequently used adverbs or adjectives via POS (Part Of Speech) tagging because POS tags representing nouns and pronouns do not have emotional relevance in this context. At last, we removed tags containing two or more words and manually filtered them by removing unrelated tags.
Then with this filtered tag based data for both before and during COVID-19, we performed Tag Emotion Induction to map tags with associated emotion. We have used a 2-dimensional Valence Arousal (VA) emotion model for this purpose. We extracted the

Embedding of tags using FastText. Then, we fed the tags' FastText embeddings into a 3-layer multi-layer perceptron, which generated VA values ranging from 1 to 9 on both dimensions. FastText embeddings are precise and include sub-word character n-grams that allow out-of-vocabulary words to be handled. Eventually we get a 2-dimensional VA vector associated with each tag to exhibit the emotions.

Next, we mapped these social tags to a broader group of tags using Geneva Emotional Music Scale (GEMS). It has 9 GEMS categories like Wonder, transcendence, nostalgia, tenderness, peacefulness, power, joyful activation, tension, and despair in which we clustered tags. Then, we produced an Emotion Prevalence Score for each user after mapping their tags to the 9 emotion categories. This indicates whether or not the user's listening history contains tags from that emotion category.

Then we performed a Wilcoxon test with and without bootstrapping to compare the before and during COVID data. Also analysis is done by plotting boxplots of scores of all the gems in both the cases for all users. Finally, we calculated static features based on VA values generated using 3-layer multi perceptron. We calculated QPS scores for all four quadrants for both datasets and compared the results with acoustic features based results.

3. Results

- 485 user’s music listening history is taken for analysis.

- Number of No-Risk users is 180 and number of At-Risk users is 120

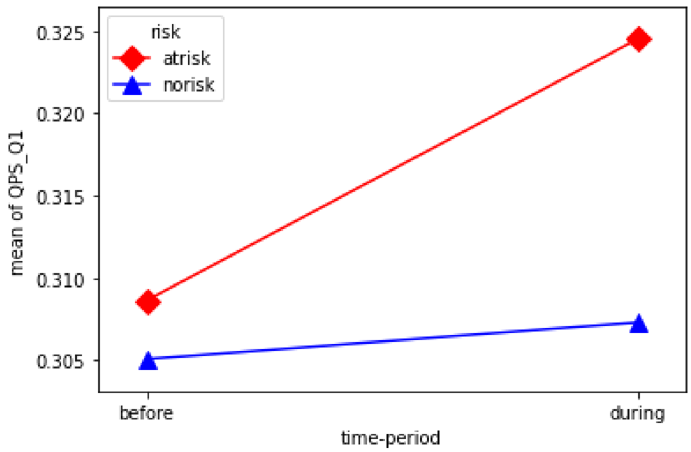
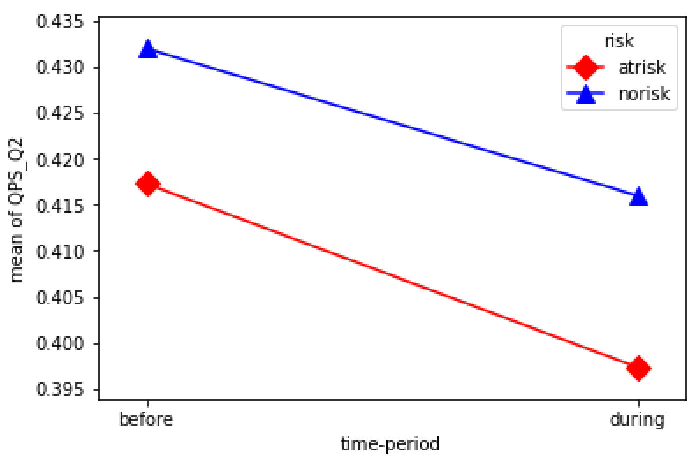
- Pre-COVID Average Number of sessions per user is 302 and average of Repetitiveness Index per user is 0.280. While Dur-COVID Average Number of sessions per user is 290 and Average of Repetitiveness Index per user is 0.293. We can see from this analysis that Average Number of sessions decreased during COVID but the sessions were long and had a high Repetitiveness Index per user during COVID19 for all users. [For more details kindly refer to Appendix Section B].

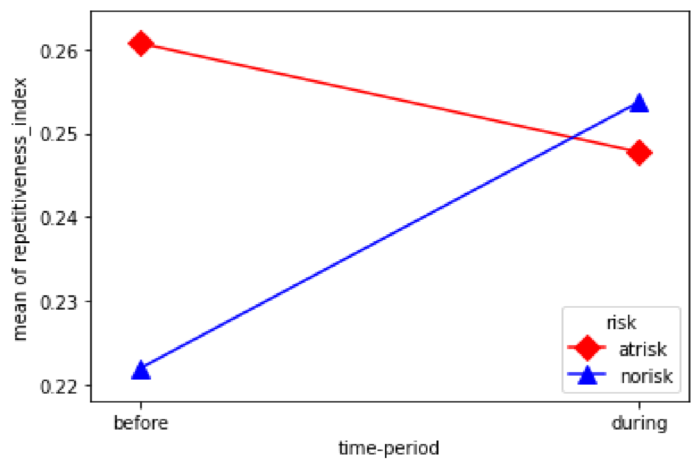
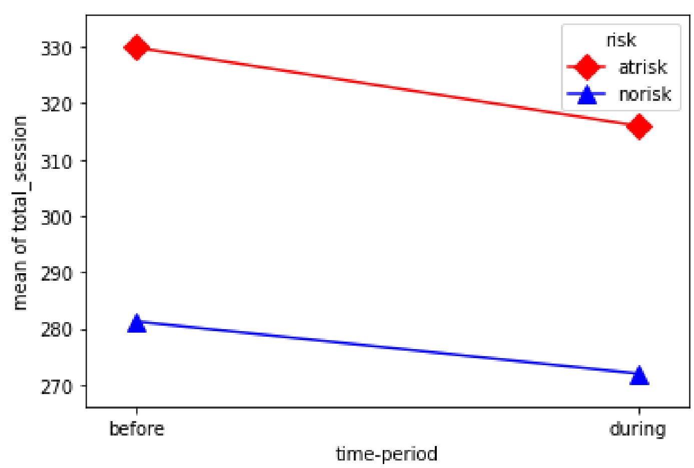
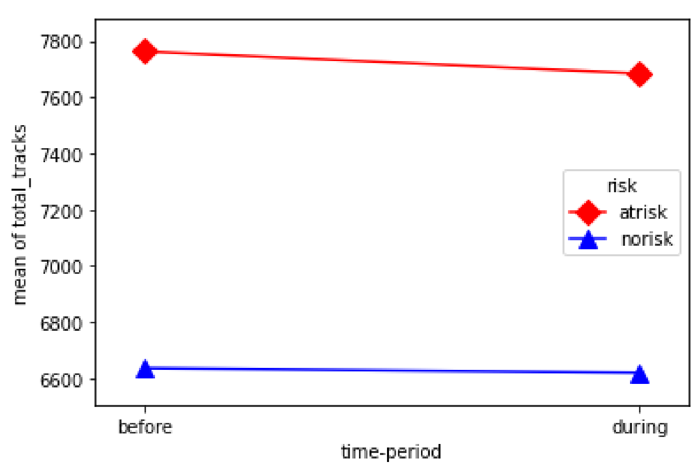
- Next, we performed a Wilcoxon signed-rank test on features to get a relationship between pre-covid and during covid data in between the features.This results in significant p-values 0.010043 and 0.010351 for QPS_Q3 and QPS_Q4 for at-risk users with autocorrelation. This showcases that for at-risk users QPS_Q3 and QPS_Q4 scores are predictable and have higher inertia and it plays an important role. Then for all users we observed that significant p_values for inertia and QPS_Q1 i.e. 0.040, static QPS_Q4 i.e. 0.023, variability with QPS_Q4 i.e. 0.005 and Liveness with variability i.e. 0.18. There are other borderline significance like danceability and speechiness with inertia. And no significant results for No-Risk users [For more details kindly refer to Appendix Section C].

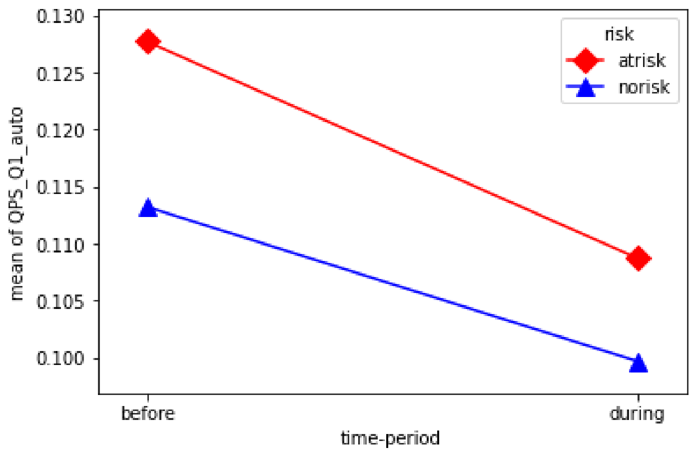
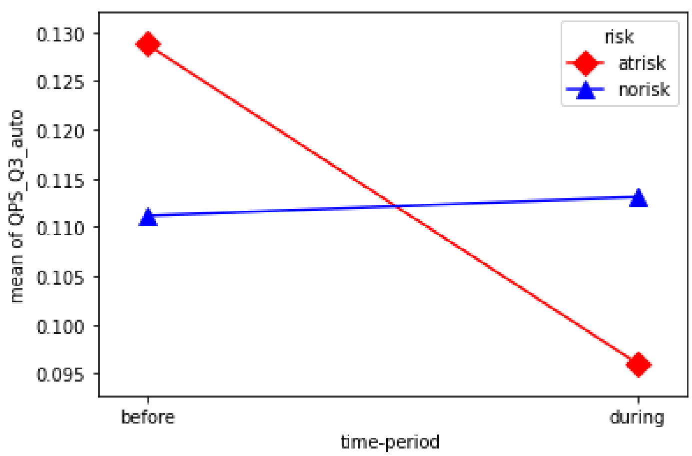
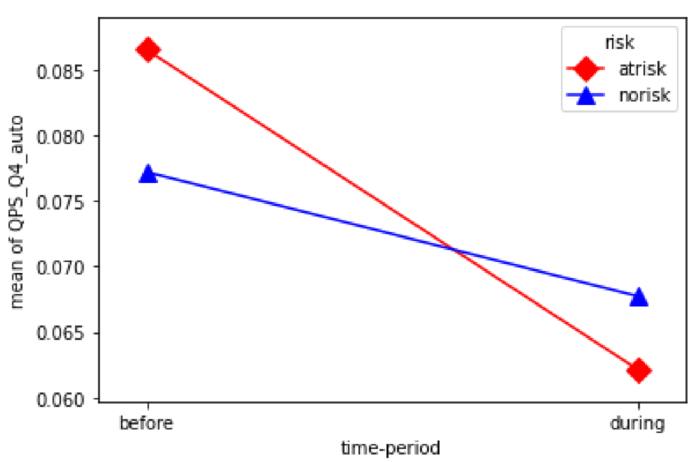
- For the period prior to COVID-19, we found positive associations between K10 and the number of sessions ($r = 0.189$, $p = 0.0002$), total play count ($r = 0.134$, $p = 0.002$), and RI ($r = 0.124$, $p = 0.005$). During COVID-19, positive associations were found between K10 and the number of sessions ($r = 0.185$, $p = 0.0003$), total play count ($r = 0.104$, $p = 0.024$), and RI ($r = 0.140$, $p = 0.001$). K10 also demonstrated a negative connection with instrumentalness variability ($r = 0.12$, $p = 0.005$). K10 also had a positive correlation with speechiness inertia ($r = 0.09$, $p = 0.03$). This showcases that instrumentalness and speechiness in music pieces are some important factors for individuals with depression. It also showcases that as the music consumption increases more and more it can lead to bad K-10 scores which are indicators for depression. [For more details kindly refer to Appendix Section D and E].

- Table below contains only significant results for Two-way Anova and their Interaction plots. Time-period (before-covid / during-covid) and risk

(At-risk/No-risk) are taken as the 2 independent variables and consider each feature as a dependent variable one at a time. [For complete table refer to Section F of Appendix].

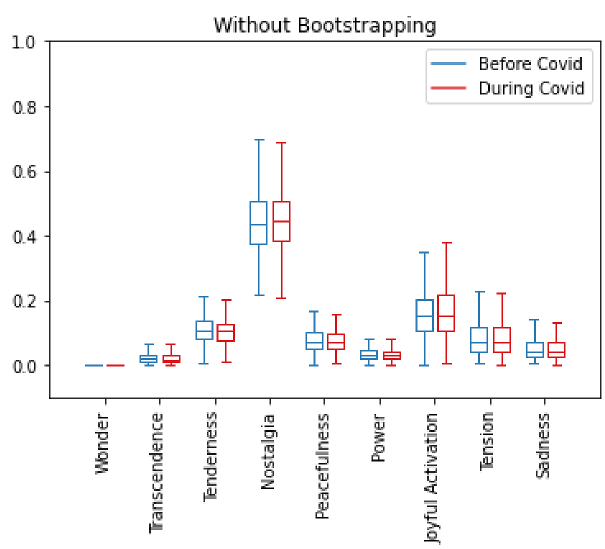
Two-way Anova Significant Results for checking interaction between Pre-COVID and Dur-COVID				
	Interaction Plots	**p(risk)**	**p(time-period)**	**p(interaction)**
QPS-Q1		0.448	0.049	0.087
QPS-Q2		0.365	0.0002	0.628

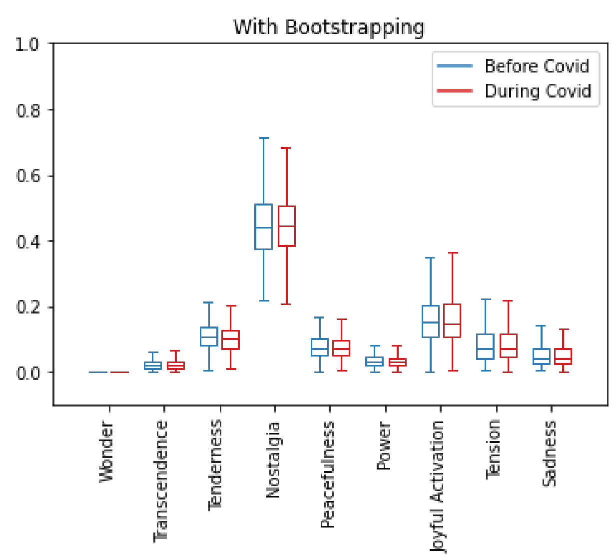
QPS-Q4		0.658	0.023	0.137
Total Sessions		0.002	0.033	0.661
Total Tracks		0.069	0.878	0.908

Inertia of QPS-Q1		0.224	0.035	0.719
Inertia of QPS-Q3		0.979	0.131	0.032
Inertia of QPS-Q4		0.847	0.071	0.393

- The p-value for static QPS Q2, which corresponds to the source as a time-period, is 0.0002. Music with high anger quality for both the groups, has decreased during COVID-19 as people tend to move towards positive emotions.

- Static QPS_Q3, we didn't find any significant difference. But on plotting Interaction Plot, we found decrease in sad songs for at risk groups in interaction effect. Which states the fact that at risk users also transitioned from sad music to more calming and peaceful music during pandemic.
- Static QPS_Q4, corresponding to source as time-period has p-value as 0.023. It is observed, there is a significant increase in the tenderness quality of music during COVID-19 for 'No Risk' group. Reason being the same positive emotion more and negative less during pandemic.
- P-value for risk and time period is significant for Total sessions that at risk users rely on music before and during COVID-19.
- Next we have analysis for the Wilcoxon test performed on GEMS data for both before and during COVID as shown in the figures below. Results have shown that both in the case of bootstrapping and without bootstrapping Tenderness has shown significant difference which is in line with our previous results that shows that all users tend to listen more and more towards calming,joyful and peaceful music to inculcate positive emotions.

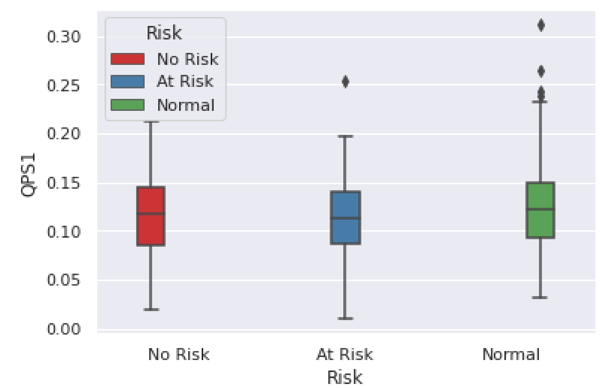


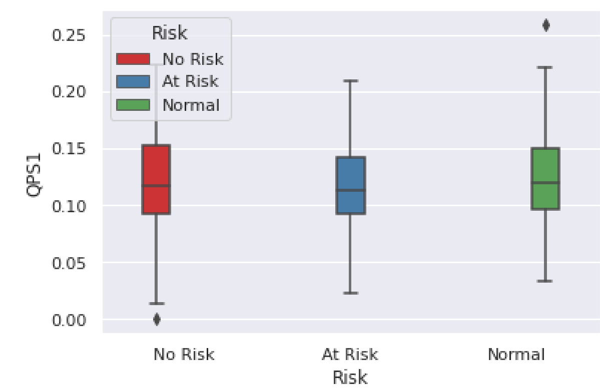


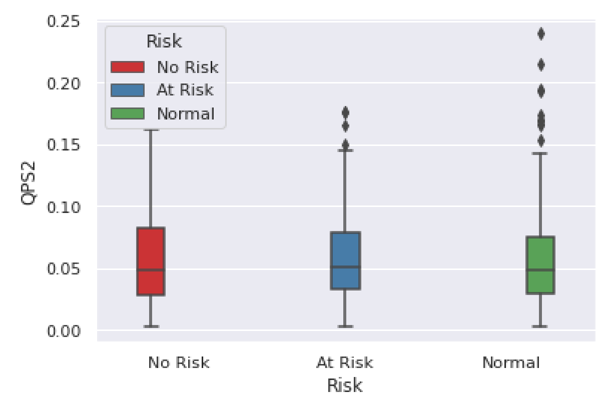
- Lastly results for QPS analysis based on emotion tags induction Valence and arousal values as shown in the table below. It showed a significant decrease in QPS_Q2 for all users and an increase in QPS_Q4 for all users. This is also inline with our previous results as it shows that anger quality of music is decreased and tenderness increased during COVID-19. [For more results kindly refer to Section H of Appendix].

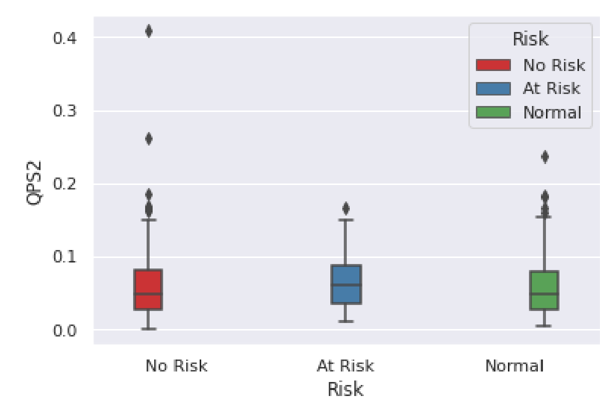
QPS Analysis Based on Emotion Tags

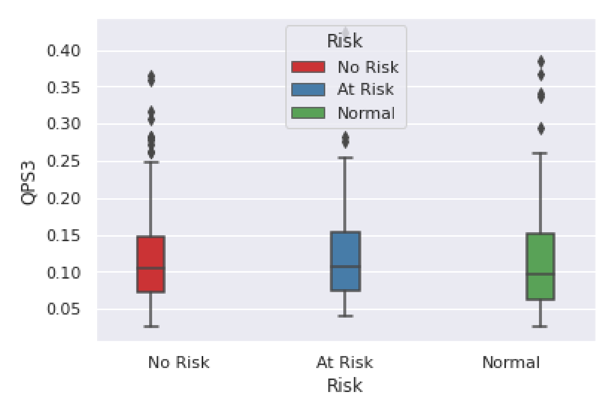
Pre-Covid Data	Dur-Covid Data

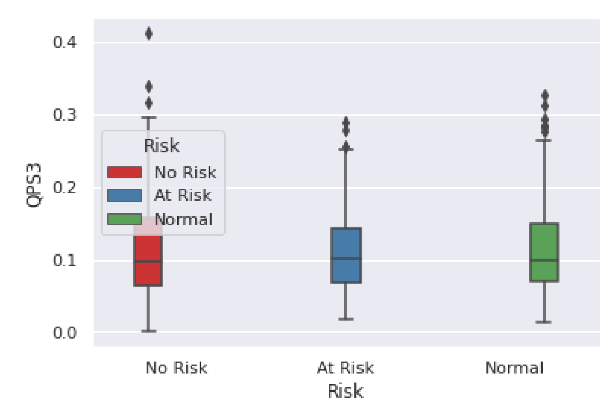


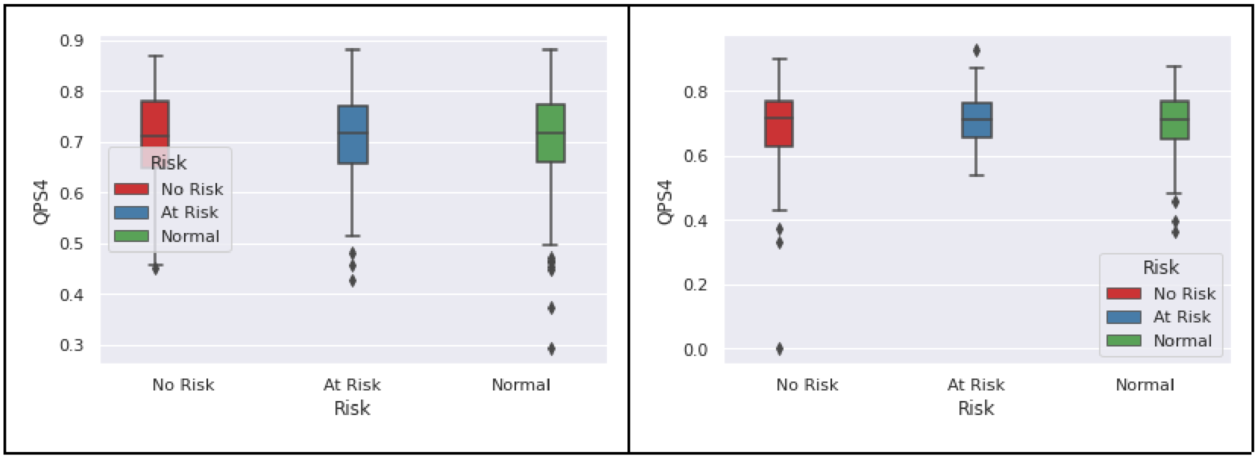











QPS4
0.9
0.8
0.7
0.6
0.5
0.4
0.3
Risk
No Risk
At Risk
Normal
No Risk
At Risk
Normal
Risk
QPS4
0.8
0.6
0.4
0.2
0.0
Risk
No Risk
At Risk
Normal
No Risk
At Risk
Normal
Risk

4. Conclusion

Individuals at-risk of depression tend to be more inclined towards music as there is a positive correlation between K10, total number of sessions and playcount (emotion focussed coping[9]). There was a significant difference in the music listening habits of the at-risk and no-risk users, especially in the emotional content of the tags. The sadness quotient in Q3 of the VA space i.e. low valence low arousal was significantly more prevalent for the at-risk users. The stronger association of the at-risk group with sadness is in accordance with the past research studies[10]. Our results also showed the same for both at-risk groups of before and during COVID-19. Also, emotional inertia and emotional variability is found to be linked with depression and ill-being[11].

Also, all users preferred listening to tender and peaceful music i.e. music with high valence low arousal. And there is a significant decrease in tense and anger evoking music i.e. music with high arousal and low valence. This means they might swivel between positive and negative emotions with mostly being in a state of low arousal. This states the fact that due to the pandemic users shifted towards music which evokes positive emotions i.e. calmness and relaxing music and decreased the music consumption of music with negative emotions like anger and fear etc.

5. Appendix

In this appendix section, we have arranged all the detailed results acquired from all the testing performed. To make it simple for any user to understand the results and get deeper insights. In the results below, we are interested in p-values which would be less than 0.05. Green indicates high significance and has p-value <= 0.05 while Orange indicates borderline significance.

A. Examples of static and dynamic feature extraction

User Summary Features - Per user feature table

Summary And Dynamic Features.ipynb

File Edit View Insert Runtime Tools Help All changes saved

```
user_summary_features
```

	sessionID	start	end	danceability	loudness	mode	speechiness	acousticness	instrumentalness	liveness	tempo	QPS_Q1	QPS_Q2	QPS_
0	1	2020-04-01 06:32:00	2020-04-01 15:03:00	0.343628	-5.644534	0.431034	0.151176	0.077087	0.435006	0.250300	129.820241	0.017241	0.913793	0.0689
1	2	2020-04-02 06:40:00	2020-04-02 19:27:00	0.335375	-5.437972	0.722222	0.130881	0.051334	0.428616	0.253817	129.809444	0.069444	0.875000	0.0555
2	3	2020-04-02 22:52:00	2020-04-02 22:59:00	0.336000	-5.552333	0.666667	0.080100	0.000007	0.644667	0.228000	119.932333	0.000000	1.000000	0.0000
3	4	2020-04-03 06:39:00	2020-04-03 17:24:00	0.379000	-6.265706	0.676471	0.104015	0.040111	0.672054	0.221585	123.802941	0.058824	0.882353	0.0588
4	5	2020-04-03 20:15:00	2020-04-03 21:02:00	0.329111	-4.014111	0.444444	0.146078	0.001747	0.489056	0.204411	136.917556	0.000000	1.000000	0.0000

Average static and dynamic features for listening history of users

```
all_user_summary.tail()
#all_user_summary.drop(all_user_summary.tail(1).index,inplace=True)
```

	user_id	K10	total_session	total_tracks	repetitiveness_index	danceability	loudness	mode	speechiness	acousticness	in
480	fdff0438dc338ba560f4d3b9bdedc4e3	14	262	3350	0.049503731930103614	0.481669	-10.376715	0.645970	0.079353	0.388005	
481	fed309c0f4f060ea787a67157f0e6a77	16	383	3770	0.023728538805150873	0.547758	-8.857262	0.784085	0.054771	0.405313	
482	ff1d102d1eaef7a14d9404a16e869e78	31	451	8633	1.8088163123256027	0.530444	-10.434797	0.621105	0.110482	0.477129	
483	ff7aefe14748d4cfed2a7f6cbc6cb226	28	454	3000	0.29771712790852944	0.543937	-7.502812	0.421667	0.050961	0.249239	
484	fc9baa2bd54e1aed22218c60f6a831e7	19	489	7652	0.07345125394643742	0.370430	-5.999008	0.614219	0.123380	0.035828	

Autocorrelation

```
all_user_autocorr.head()
```

	user_id	K-10	danceability	loudness	mode	speechiness	acousticness	instrumentalness	liveness	tempo	QPS_Q1	QPS_Q2
0	05157feb07f9e780637ffb96ae549365	38	0.036753	0.012497	0.092193	0.198493	0.032450	0.126769	-0.008440	0.071468	0.087669	0.017955
1	06bd850533a713bb7800766860dc6e6e	22	0.200379	0.162489	0.049703	0.155538	0.091320	0.142868	0.219916	0.070931	-0.019023	0.057256
2	03e7c2869742ac3b8b04a45675ab5b24	12	0.212409	0.192599	0.088977	0.194389	0.285146	0.200652	0.049879	0.172934	0.259115	0.082721
3	0538da9949fdaa2da6e5f18c0a27e146	30	0.139427	0.155880	0.012925	0.044748	0.127531	0.047814	0.056455	-0.005651	0.024583	0.050533
4	03c38064fb423b47d5292bffc09785cc	19	0.139628	0.195127	0.163588	0.048842	0.090204	0.085517	0.138682	0.039550	0.148056	0.063424

Variability

```
all_user_variability.head()
```

	user_id	K-10	danceability	loudness	mode	speechiness	acousticness	instrumentalness	liveness	tempo	QPS_Q1	QPS_Q2
0	05157feb07f9e780637ffb96ae549365	38	0.105606	2.689329	0.220432	0.043154	0.174171	0.217813	0.071304	11.751355	0.213665	0.277740
1	06bd850533a713bb7800766860dc6e6e	22	0.101556	2.618071	0.258939	0.033227	0.168973	0.182093	0.168618	13.808500	0.292232	0.324589
2	03e7c2869742ac3b8b04a45675ab5b24	12	0.081767	2.645149	0.146357	0.050171	0.154996	0.198674	0.050484	9.643929	0.144777	0.150591
3	0538da9949fdaa2da6e5f18c0a27e146	30	0.117242	2.766052	0.236219	0.075992	0.199739	0.183923	0.080559	15.382950	0.270806	0.261411
4	03c38064fb423b47d5292bffc09785cc	19	0.117222	3.070857	0.267048	0.036650	0.198486	0.239705	0.131624	14.915816	0.287767	0.306521

B. Results for Average Analysis for Users

For All Users Pre-COVID -

- Average Number of sessions per user : 302.245
- Average Number of tracks per user : 6928.878
- Average of RepetitivenessIndex per user : 0.280

For All Users Dur-COVID -

- Average Number of sessions per user : 290.499
- Average Number of tracks per user : 7130.796
- Average of RepetitivenessIndex per user : 0.293

For No-Risk Users Pre-COVID -

- Average Number of sessions per user : 281.239
- Average Number of tracks per user : 6635.8
- Average of RepetitivenessIndex per user : 0.222

For No-Risk Users Dur-COVID -

- Average Number of sessions per user : 271.961
- Average Number of tracks per user : 6619.811
- Average of RepetitivenessIndex per user : 0.254

For At-Risk Users Pre-COVID -

- Average Number of sessions per user : 329.9
- Average Number of tracks per user : 7762.825
- Average of RepetitivenessIndex per user : 0.248

For At-Risk Users Dur-COVID -

- Average Number of sessions per user : 315.975
- Average Number of tracks per user : 7684.308333333333
- Average of RepetitivenessIndex per user : 0.261

C. Results for Wilcoxon signed-rank test on features to get a relationship between pre-covid and during covid data.

Relationship between Static features and Dynamic features for At Risk Users			
Property	**p_value**	**p_value (autocorr)**	**p_value(variability)**
Danceability	0.441331	0.087243	0.93113
Loudness	0.616931	0.671379	0.624326
Mode	0.731544	0.677117	0.180818
Speechiness	0.553941	0.162757	0.680953
Acousticness	0.733515	0.271365	0.639229
Instrumentalness	0.842236	0.216419	0.555697
Liveness	0.83405	0.947798	0.113099
Tempo	0.977018	0.866892	0.221325
QPS_Q1	0.402009	0.120426	0.189502
QPS_Q2	0.240694	0.763285	0.552189
QPS_Q3	0.663757	0.010043	0.557454
QPS_Q4	0.763285	0.010351	0.552189
Total_tracks	0.395418	-	-
Total_sessions	0.754315	-	-
Repetitive_Index	0.956141	-	-

Relationship between Static features and Dynamic features for No Risk Users			
Property	**p_value**	**p_value (autocorr)**	**p_value(variability)**
Danceability	0.346514	0.289173	0.327115
Loudness	0.184015	0.469794	0.311157
Mode	0.693387	0.053444	0.220333
Speechiness	0.863895	0.242029	0.944197
Acousticness	0.469794	0.102519	0.173855
Instrumentalness	0.87514	0.263351	0.637354
Liveness	0.851557	0.752233	0.217123
Tempo	0.672418	0.813665	0.309114
QPS_Q1	0.885282	0.280807	0.460194
QPS_Q2	0.416327	0.277634	0.193627
QPS_Q3	0.675547	0.776204	0.226855
QPS_Q4	0.078183	0.550435	0.104031
Total_tracks	0.355835	-	-
Total_sessions	0.949314	-	-
Repetitive_Index	0.758748	-	-

Relationship between Static features and Dynamic features for All Users			
Property	**p_value**	**p_value (autocorr)**	**p_value(variability)**
Danceability	0.562484	0.063409	0.22929
Loudness	0.087097	0.70298	0.327382
Mode	0.560519	0.327062	0.100133
Speechiness	0.825086	0.066132	0.87967
Acousticness	0.295511	0.248391	0.06272
Instrumentalness	0.572356	0.434863	0.243384

Liveness	0.756515	0.101613	0.018282
Tempo	0.685046	0.673423	0.141126
QPS_Q1	0.313348	0.040845	0.083395
QPS_Q2	0.100736	0.262601	0.234219
QPS_Q3	0.835691	0.186382	0.106297
QPS_Q4	0.023061	0.167297	0.005871
Total_tracks	0.122769	-	-
Total_sessions	0.947717	-	-
Repetitive_Index	0.708514	-	-

D. Results for Spearman correlations between K10 and all 485 user's Number of Sessions, Total Play Count and RI. Below are the two tables for Pre-COVID and During COVID.

R-value and p-value between K10 and Number of Sessions, Total Tracks and RI for Pre-COVID		
Property	**r-value**	**p-value**
Total Session	0.1919	0.00002
Total Tracks	0.1359	0.0026
RI	0.1287	0.0045

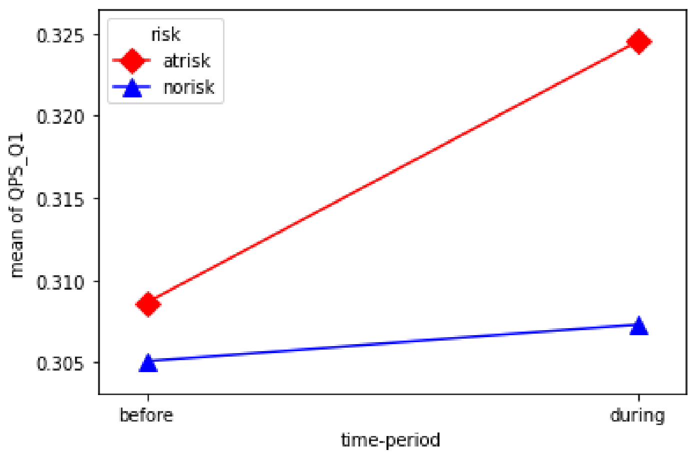
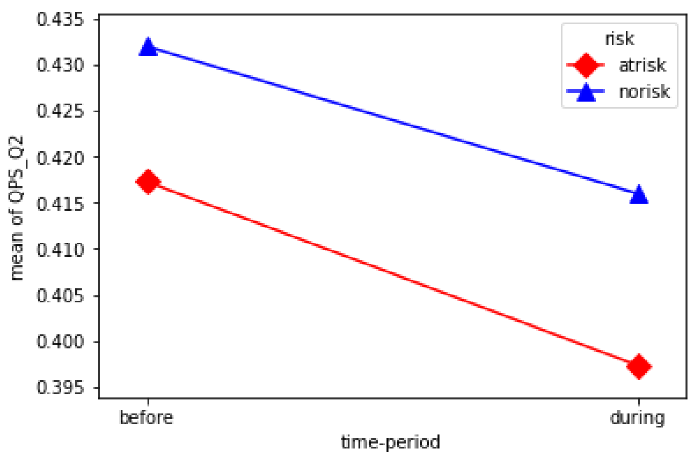
R-value and p-value between K10 and Number of Sessions, Total Tracks and RI for Dur-COVID		
	r-value	**p-value**
Total Session	0.1885	0.00002
Total Tracks	0.1046	0.0211
RI	0.0015	0.0015

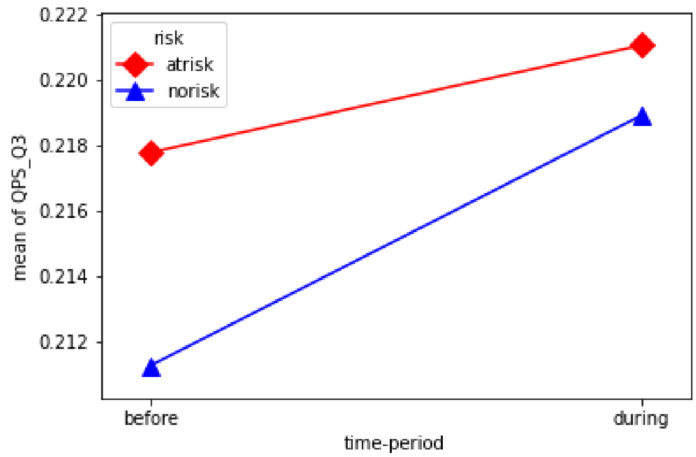
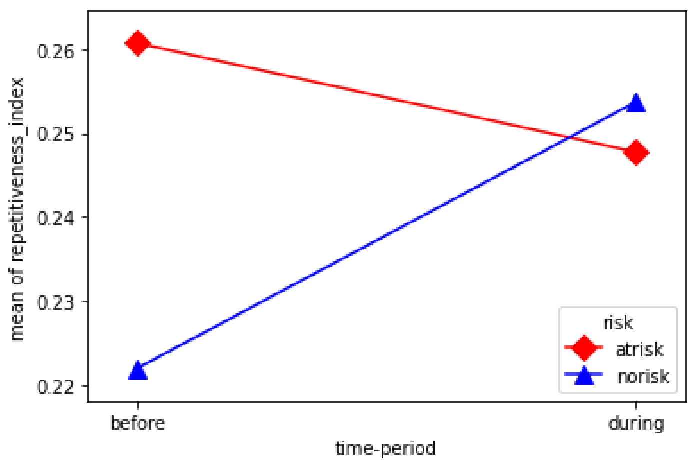
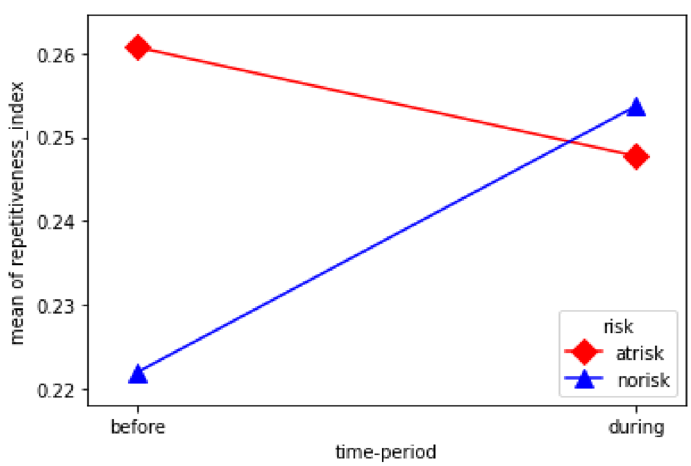
E. **Similarly, correlation between K10 and each of the dynamic measures of audio and emotion features was computed.**

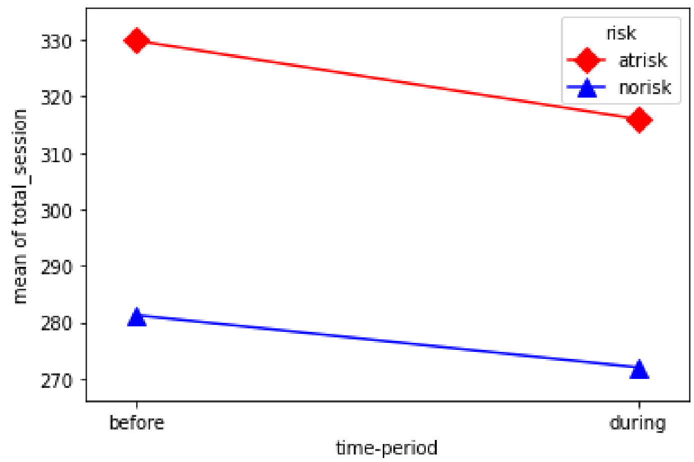
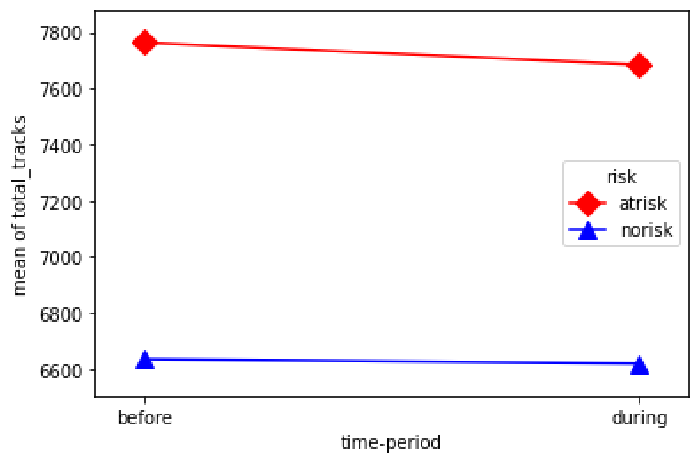
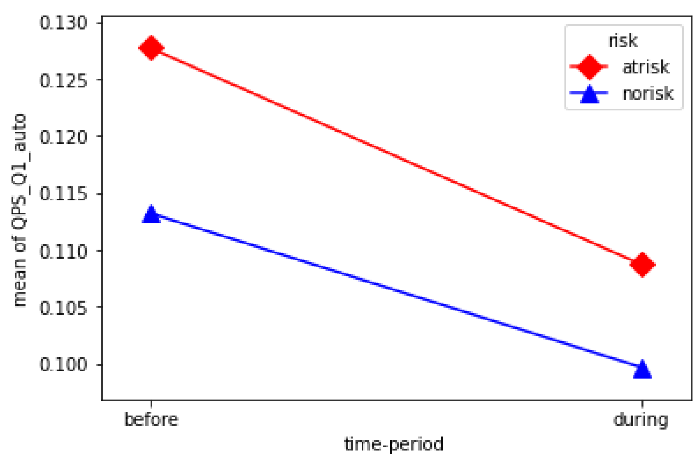
Correlation between K10 and each of the dynamic measures of audio for Pre-COVID				
	r_var	**p_var**	**r_iner**	**p_iner**
danceability	0.027059	0.552188	-0.043582	0.338176
loudness	0.02896	0.524602	0.000049	0.999134
mode	0.057856	0.2034	-0.060182	0.185789
speechiness	0.087859	0.053158	0.04346	0.339535
acousticness	0.023829	0.600633	0.021728	0.633125
instrumentalness	0.001882	0.967029	-0.125976	0.005465
liveness	0.042161	0.35418	-0.064866	0.153773
tempo	0.039096	0.39028	-0.052303	0.250278
QPS_Q1	0.022651	0.618759	-0.062571	0.16889
QPS_Q2	-0.03599	0.42905	-0.061532	0.176089
QPS_Q3	0.092611	0.041484	0.02363	0.603677
QPS_Q4	0.04517	0.320857	0.028734	0.52784

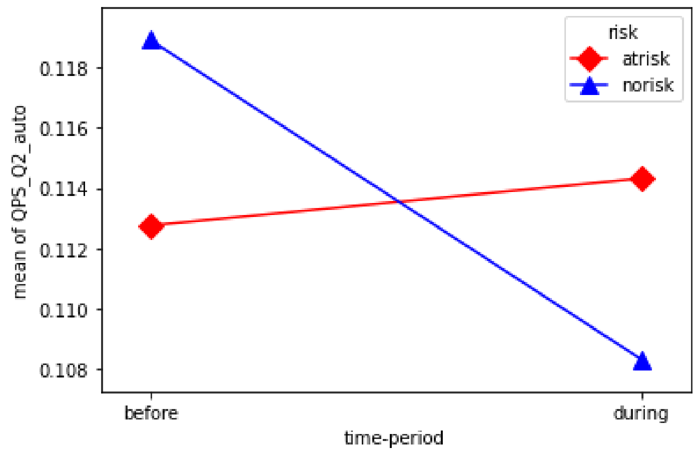
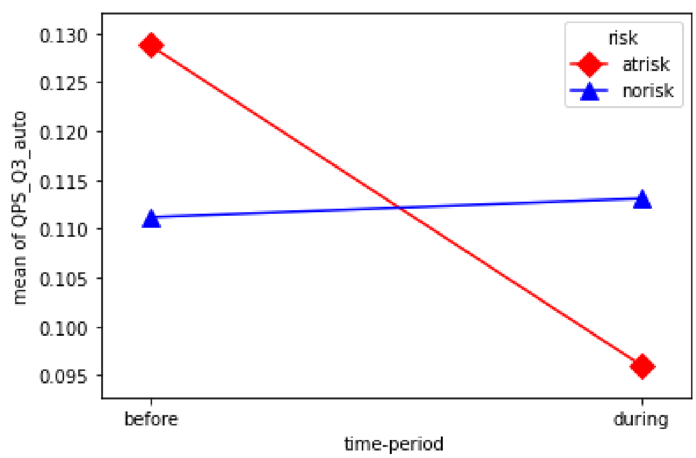
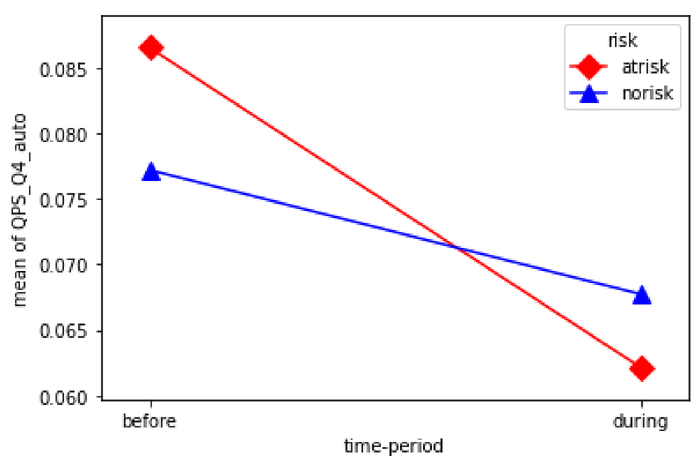
Correlation between K10 and each of the dynamic measures of audio for Dur-COVID				
	r_var	**p_var**	**r_iner**	**p_iner**
danceability	0.012249	0.787871	-0.040292	0.375935
loudness	0.001624	0.971537	-0.031803	0.484709
mode	0.139838	0.002023	-0.024591	0.589033
speechiness	0.050308	0.268832	0.075835	0.09528
acousticness	0.000102	0.998218	-0.003573	0.937449
instrumentalness	-0.011769	0.796	-0.079713	0.079472
liveness	0.054099	0.234359	-0.023196	0.610347
tempo	-0.021824	0.631626	-0.015888	0.727085
QPS_Q1	-0.002594	0.954564	-0.008917	0.844709
QPS_Q2	-0.027	0.553051	-0.069733	0.125124
QPS_Q3	-0.015707	0.730057	0.006913	0.879312
QPS_Q4	0.005207	0.908945	-0.004616	0.919244

F. **Results for Two-way Anova and Interaction plots. Time-period (before-covid / during-covid) and risk (At-risk/No-risk) as the 2 independent variables and consider each feature as a dependent variable one at a time.**

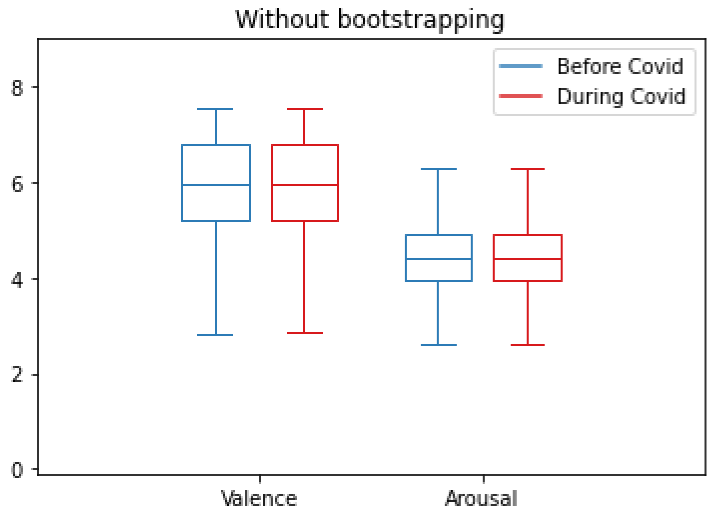
Two-way Anova Results for checking interaction between Pre-COVID and Dur-COVID				
	Interaction Plots	**p(risk)**	**p(time-period)**	**p(interaction)**
QPS-Q1		0.448	0.049	0.087
QPS-Q2		0.365	0.0002	0.628

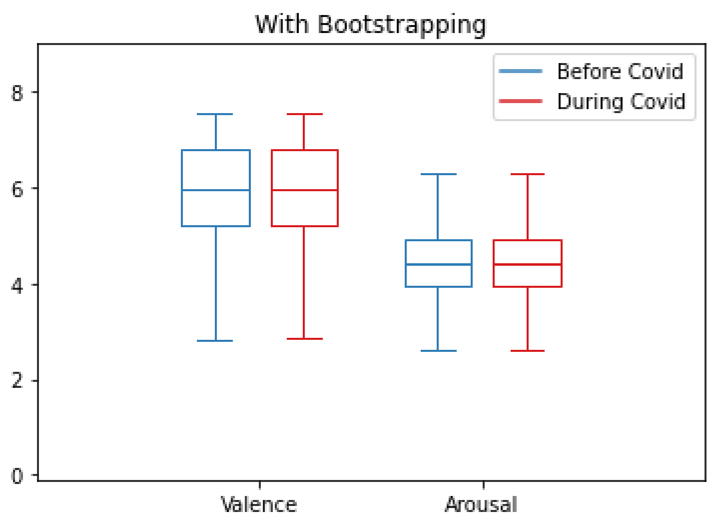
QPS-Q3		0.760	0.201	0.642
QPS-Q4		0.658	0.023	0.137
RI		0.660	0.521	0.311

Total Sessions		0.002	0.033	0.661
Total Tracks		0.069	0.878	0.908
Inertia of QPS-Q1		0.224	0.035	0.719

Inertia of QPS-Q2		0.993	0.414	0.396
Inertia of QPS-Q3		0.979	0.131	0.032
Inertia of QPS-Q4		0.847	0.071	0.393

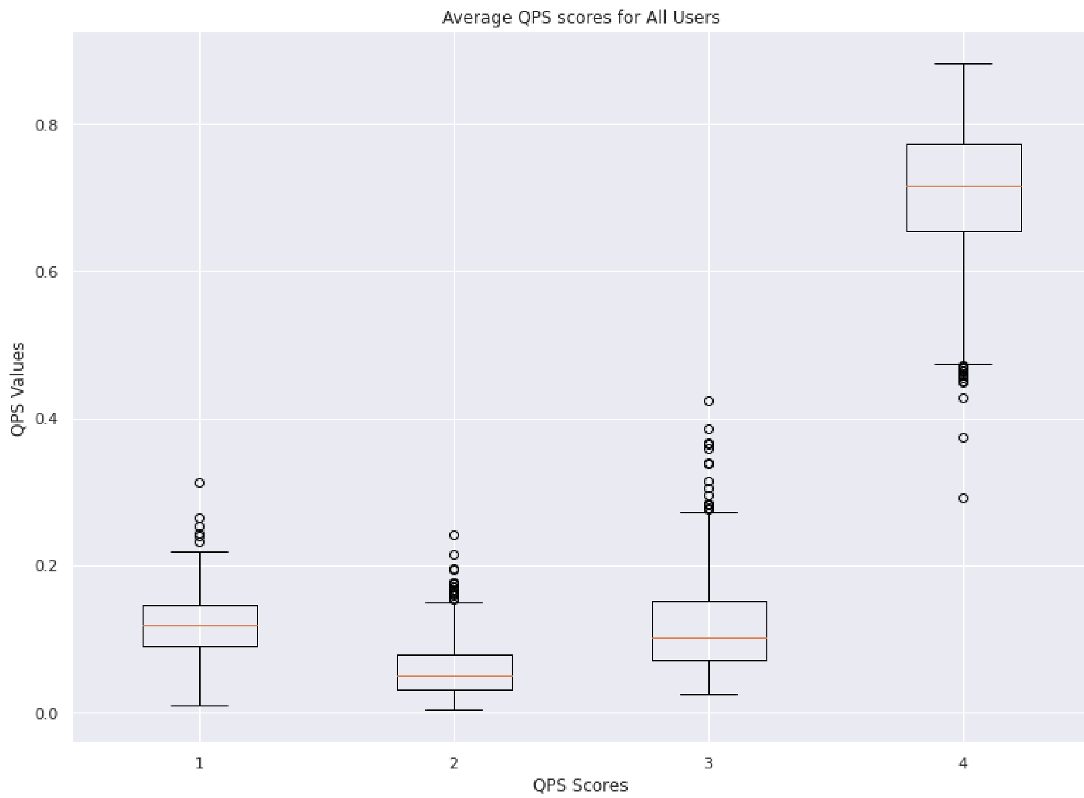
G. Analysis for Wilcoxon test performed on emotion tags Pre-COVID and Dur-COVID with and without bootstrap. Some of the significant results are in Results section.

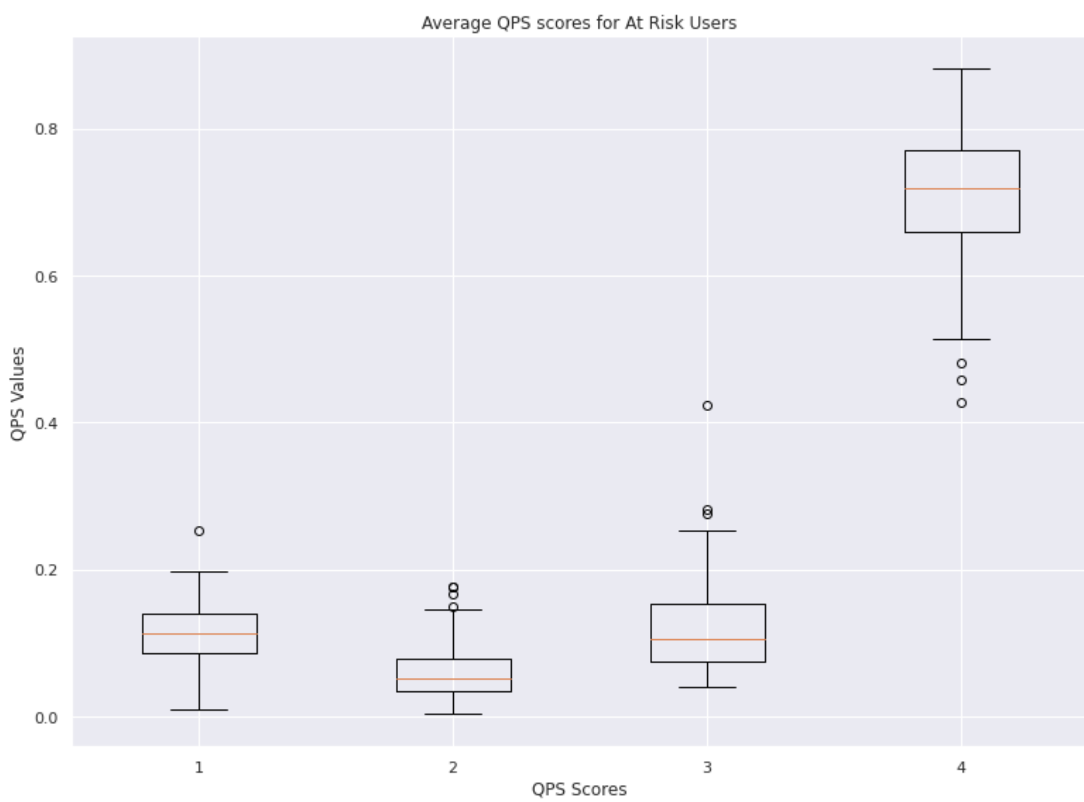


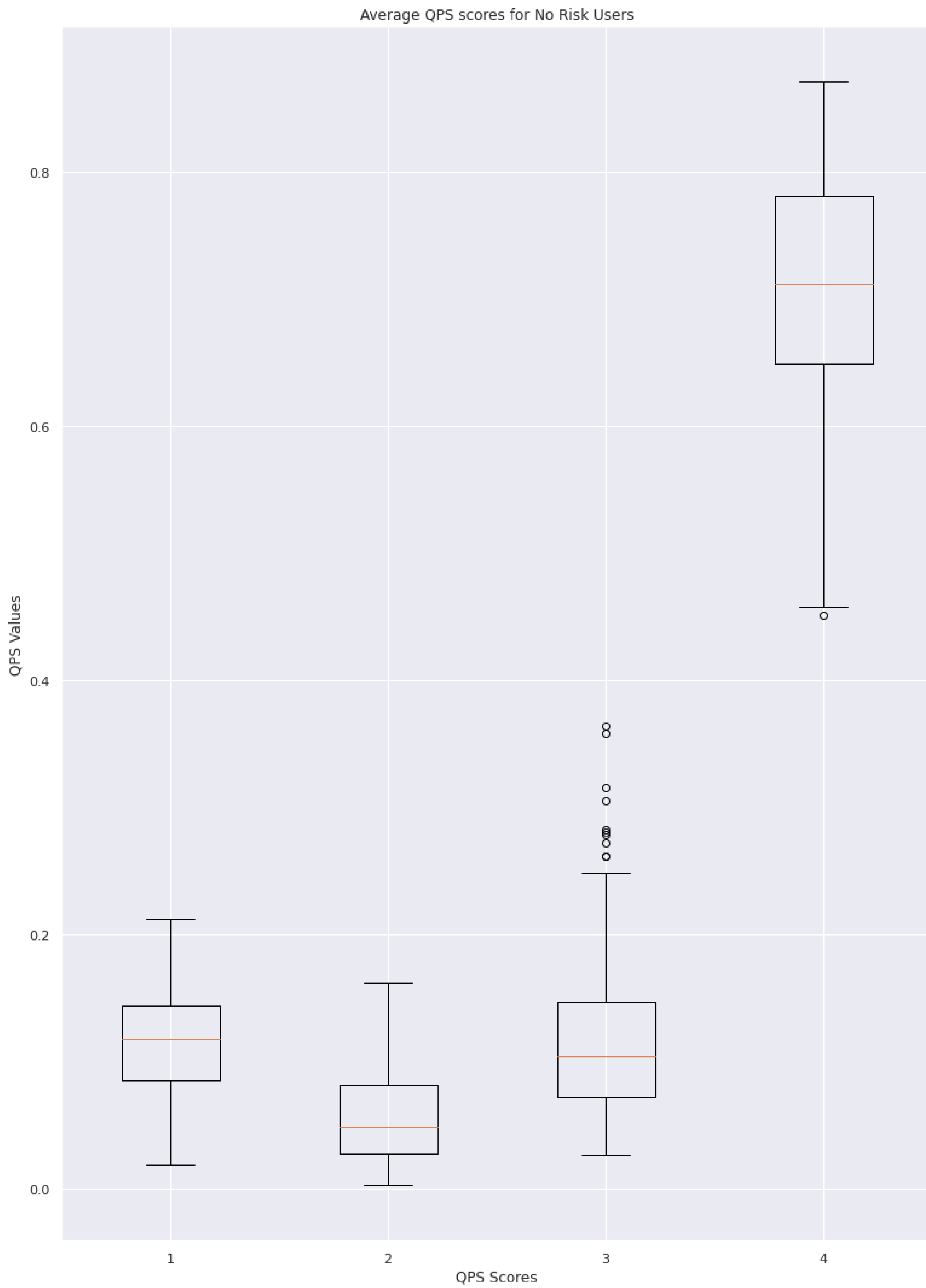


H. QPS Analysis based on emotion tags and VA values generated by tag emotion induction.

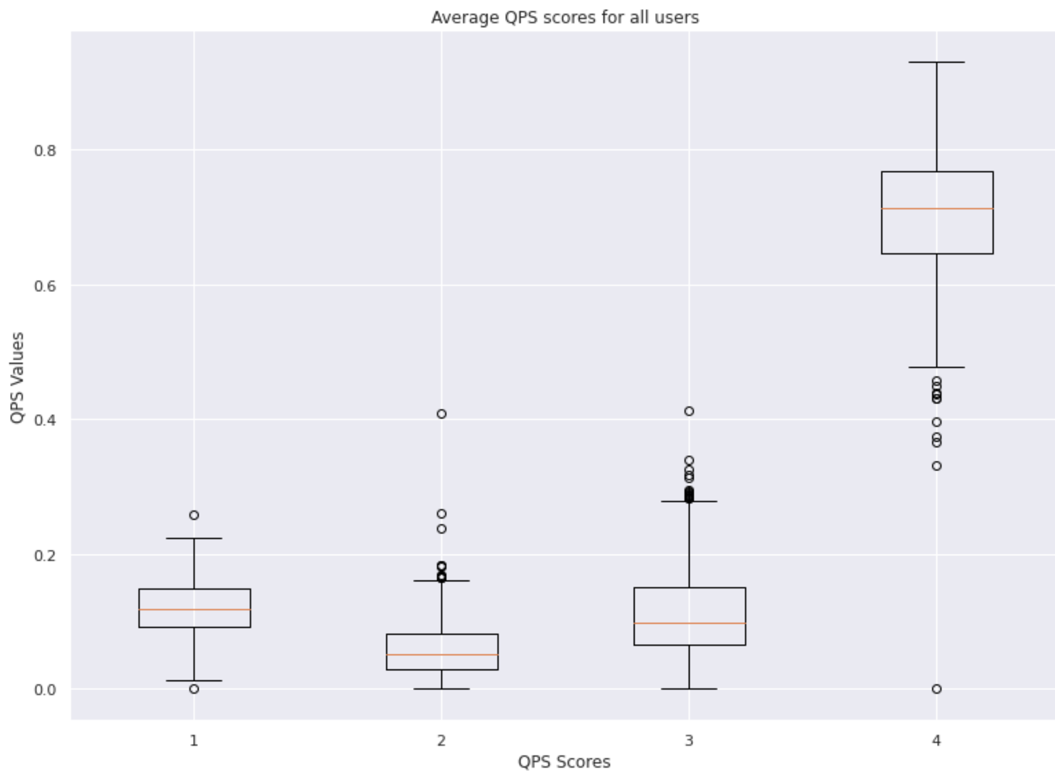
Results of Pre-Covid QPS Analysis

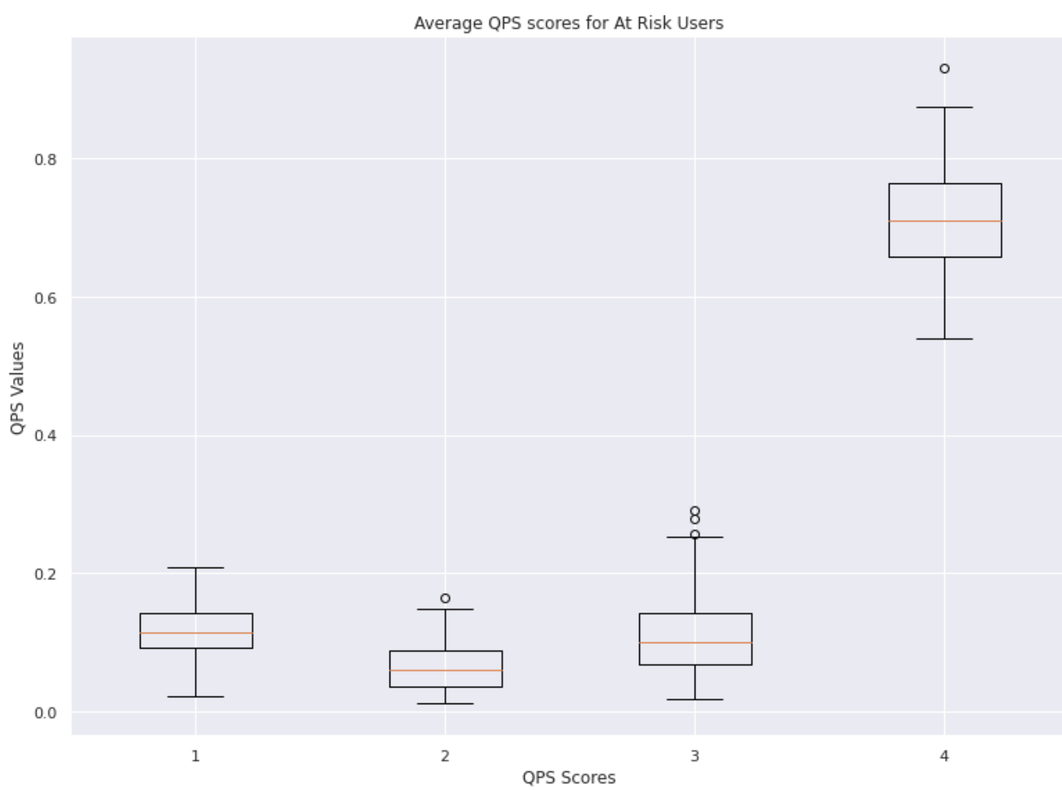

Average QPS scores for All Users
QPS Values
0.0
0.2
0.4
0.6
0.8
1
2
3
4
QPS Scores

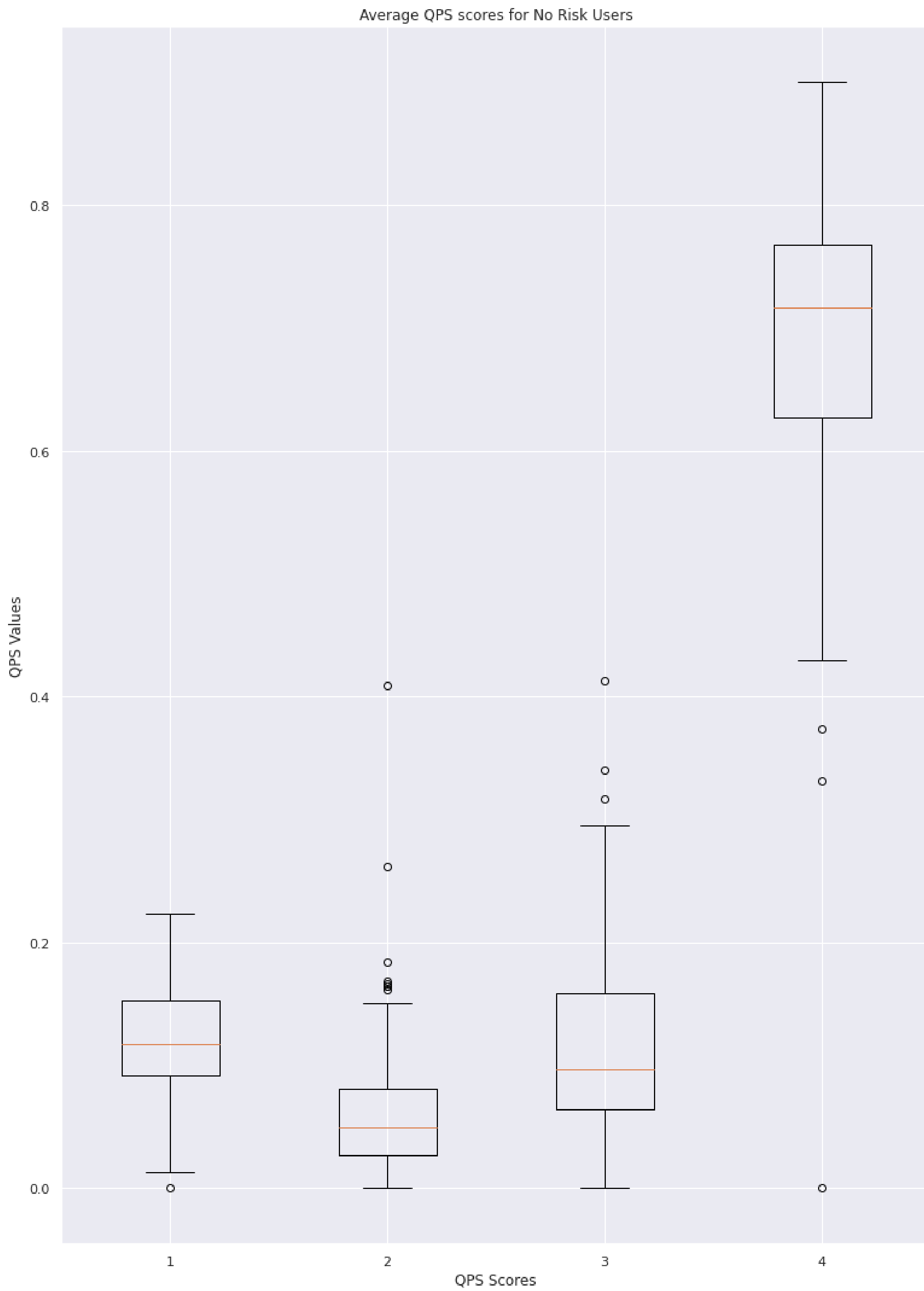

Average QPS scores for At Risk Users
QPS Values
0.0
0.2
0.4
0.6
0.8
1
2
3
4
QPS Scores


Average QPS scores for No Risk Users
QPS Values
0.0
0.2
0.4
0.6
0.8
1
2
3
4
QPS Scores

Results of Dur-Covid QPS Analysis






Average QPS scores for No Risk Users
QPS Values
0.0
0.2
0.4
0.6
0.8
1
2
3
4
QPS Scores

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