Changes in General and Virus-Specific Anxiety during the Spread of COVID-19 In Israel: A Seven-Wave Longitudinal Study.

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ABSTRACT

We compared three hypothetical trajectories of change in both general and COVID-19-specific anxiety during the 1st wave of the spread in the state of Israel: panic (very high anxiety, either from the outset or rapidly increasing), complacency (stable and low anxiety), and threat-sensitive (a moderate, linear increase compatible with the increase in threat). A representative sample of 1018 Jewish-Israeli adults was recruited online. A baseline assessment commenced two days *prior to* the identification of the first case, followed by six weekly assessments. Latent Mixture Modeling analyses revealed the presence of the three trajectories: (1) "threat-sensitivity" (29% and 66%, for general and virus-specific anxiety, respectively), (2) Panic (12% and 25%), and (3) Complacency (29% and 9%). Only for general anxiety, a fourth class representing a stable mid-level anxiety was identified ("balanced": 30%). For general anxiety, females and the initially anxious - both generally and specifically from the spread of the virus - were more likely to belong to the panic class. Men and older participants were more likely to belong to the

complacency class. Findings indicate a marked heterogeneity in anxiety responses to the first wave of the spread of COVID-19, including a large group evincing a "balanced" response.

Key Words: COVID-19, Anxiety, Israel, Trajectories, Prospective Study.

Abbreviations:

COVID-19: Corona Virus Infectious Disease, 2019 (Abstract and text).

COVID-19-IPBP: COVID-19 Israeli Public Behavior Project (Text).

H1N1: Influenza A Virus Subtype.

IMOH: Israeli Ministry of Health (Text).

WHO: World Health Organization (Text).

GA: General Anxiety (Tables).

VSA: Virus Specific Anxiety (Tables).

Statistical Abbreviations:

LCGA: latent class growth analyses.

GMM: growth mixture models.

GRoLTS-Checklist: Growth latent trajectory studies.

RMSEA: Root Mean Square Error of Approximation.

CFI: Confirmatory Fit Index.

TLI: Tucker-Lewis Index.

SPMR: Standardized Root Mean Square Residual.

VCV: Variance-Covariance.

LMR: Lo-Mendell-Rubin test.

bLRT: Bootstrapped Likelihood Ratio Test.

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INTRODUCTION

On December 2019, the first cases of Corona Virus Disease 2019 (COVID-19) were identified in Wuhan, China.[1] The outbreak was declared a Public Health Emergency of International Concern on 30 January and as a global pandemic on March 11, 2020. COVID-19 commonly present as cold symptoms (cough ,fever, malaise, myalgias), gastrointestinal symptoms, and anosmia, but may exacerbated into shortness of breath, severe pneumonia, respiratory failure and death. Men, the elderly and people with pre-existing medical conditions are most vulnerable to severe illness.[2] As of writing these words, during July, 2021, effective vaccines are used to prevent the spread of COVID-19, and Israeli is leading in terms of offering them to the public. Up until the emergence of these vaccines, however, the only preventive treatment was behavioral, and includes hygiene, physical-distancing, masks-wearing, and large-scale societal measures ranging from targeted quarantine to general lockdowns.[3,4]. Because some variants of COVID-19 appear to challenge even the more effective vaccines, such behavioral measures are still highly pertinent to the aim of containing the spread of the virus.

Two unique characteristics of the State of Israel render this state an interesting avenue for studying public responses to the spread of COVID-19. The first is Israeli resilience in the face of mass emergencies. Unlike most other Western countries, the Israeli public is extensively experienced with emergency situations, almost all of them military. The Israeli public has repeatedly demonstrated elevated compliance and community/national resilience, manifested, for instance, by moderate levels of anxiety in the face of repeated missile attacks on civilians [5].

The second unique Israeli characteristic is a strong social-health system. Israel's health system is built upon welfare/social-medicine foundations, with all citizens being health-ensured by law and the Israeli Health Maintenance Organizations having immediate access to all

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segments of the society. In fact, Israel was the state pioneering the employment of a highly successful mass vaccination campaign using the vaccine developed by Pfizer, and this enabled the opening of commerce and cultural life. Arguably, the ability of Israeli citizens to rely on the healthcare system to provide them with necessary care and reduce the risks associated with Covid-19 likely reduced some of the stress and anxiety related to the uncertainty associated with the pandemic.

This is the 1st report from the COVID-19-Israeli Public Behavior Project (COVID-19-IPBP), a project aimed at documenting the Israeli public's reaction to the pandemic, with a focus on compliance, public trust, resilience, and emotional distress. An integrated conceptual framework guiding this study was utilized, drawing from behavioral medicine, psychology and psychiatry, and public health. In this first report from COVID-19-IPBP, we utilized data from the 1st wave of the spread (although we have been, and still are, collecting data). Herein we report on the Israeli public's *anxiety,* a key factor in populations' behavior during medical crises such as mass-vaccination, plagues, and global hostilities [6].

Anxiety is largely considered a negative force, usually a clinical outcome of the crisis [7]. It is construed as an alarming outcome among medical teams [8], as well as a factor derailing the public's compliance with instructions issued by policy makers [7]. Importantly, some levels of fear which are compatible with the medical threat are expected in the public, and some levels of anxiety can act to positively encourage people to adhere to guidelines. Nevertheless, extreme levels of fear and anxiety, tantamount to "panic", are likely to exacerbate the spread of epidemics and pandemics [9]. At the same time, low levels of anxiety may be associated with an under-estimation of the medical threat, and often represent "complacency" [10,11]. The latter might hinder

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preparedness [10], and compliance with governments' instructions, such as those concerning social distancing [11].

Because most pandemic-anxiety research is cross-sectional, not enough is known about trajectories of public anxiety during pandemics. However, one longitudinal study revealed that, in response to the H1N1 pandemic, anxiety increased rapidly, but then rapidly decreased [12]. Moreover, responses to the Ebola *epidemic* (distinguishable from H1N1 and COVID-19, which are pandemics) appear to reflect immediately high anxiety that was increasing further [13].

We investigated a large cohort of Jewish-Israeli adults over six weeks, using seven weekly assessments. The first assessment (Wave 0) transpired two days *prior* to the identification of the first COVID-19 carrier in Israel. We assessed general and virus-specific anxiety, demographics, and other variables not pertinent to the present report. Charting changes in general vs. virus-specific anxiety, we compared three hypothetical models:

(1) *A "Panic Model",* evincing extreme levels of anxiety, either starting at a low level and increasing very fast or as high anxiety already appearing from the outset.

(2) A *"complacency model"*, in which general and virus-specific anxiety start and stay relatively low, i.e., not exceeding the mid-level of the scales.

(3) *A "threat-sensitivity model",* a title developed specifically for this study. This model reflects a linear increase in anxiety which is commensurate with the increase in the threat (see [9]).

It should be noted that all three possibilities – and of course additional ones – may occur *concurrently* at any single population, reflecting a heterogeneous public response to COVID-19. We allowed for this possibility in our analyses (see below).

To summarize, the three goals of the present study are:

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(1) To identify various trajectories of anxiety in the investigated population during the 1st wave of the spread of COVID-19 in Israel.

(2) To characterize individuals belonging to the various trajectories using baseline anxiety and demographic variables.

(3) To examine the direction of relationships between general and virus-specific anxiety. We were particularly interested in examining the predictive effect of baseline virus-specific anxiety on trajectories of general anxiety. Such an effect would suggest that at least some of the change in general anxiety during the 1st wave of the spread is attributable to the spread itself, rather than to preexisting conditions.

METHODS

Participants and procedure.

COVID-19-IPBP was approved by the Ethics Committee of the Department of Psychology of Ben- Gurion University. Participants were recruited through the MIDGAM Project Web Panel, an Israeli company specializing in internet research (see **Web Appendix 1**). MIDGAM has access to hundreds of thousands of Israelis interested in participating in online studies, either voluntarily or in exchange for monetary reimbursement.

Seven weekly assessments were employed, each assessment wave lasting for 24-hours. *The first assessment wave*, i.e., Week 0, took place on February the 19th, 2020, when IG (Then serving as Deputy Director General of the Israeli Ministry of Health [IMoH]) was in Japan, conducting tests of Israeli passengers on board of the Diamond Princess Cruise Ship. At that time, there were *no known carriers* of COVID-19 in Israel, although the expectation was that those will be detected in a matter of days. Participants were 1018 adults largely representing the Israeli-Jewish population in terms of sex and age (see **Web Tables 1-4**). The recruitment procedure is depicted in **Figure 1.**

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The second assessment wave, i.e., Week 1, took place on February the 25th, 2020. At that time, two Israelis were reported to be infected, most likely by visiting pilgrims from South Korea. As well, an infected Israeli returning from Italy was identified after visiting various places in the country and spreading the virus. The Israeli Ministry of Health issued a recommendation against traveling to Hubei County in China.

The third assessment wave, i.e., Week 2, took place on March the 4th, 2020. Then, 16 infected individuals were identified. The MoH issued instructions to Israelis returning from Italy, France, Spain, Austria, Germany, and Switzerland.

The fourth assessment wave, i.e., Week 3, took place on March the 11th, 2020. Ninety-nine infected individuals were identified. Two people were hospitalized. Gatherings of >100 people were prohibited, and people younger than 65 are instructed to refrain from visiting the elderly.

The fifth assessment wave, i.e., Week 4, took place on March the 18th, 2020, after 524 “cases” were identified. All Israelis arriving from other countries were instructed to be self-quarantined. The education system was inoperative. Gathering of >10 people was prohibited. Lockdowns was placed on targeted areas were spread was high.

The sixth assessment wave, i.e., Week 5, took place on March the 25th, 2020, after 2436 “cases” were identified. One hospitalized patient died from the virus. People were instructed to minimize outings to strictly crucial activities, otherwise not to leave home for more than 100 meters. Group praying ("Mynian") was prohibited.

The seventh assessment wave, i.e., Week 6, took place on April 1st, 2020, several days prior to the Passover holiday and after 6168 “cases” were identified. Prohibitions and guidelines were dramatically increased, and were enforced thereafter (e.g., fines for not wearing masks).

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Measures.

All measures were self-report questionnaire items. Following Israeli et al [5], *General anxiety* was assessed by averaging two items taken from the State Anxiety Inventory (SAI; items 3 and 9) [14]. Responses are provided on a 5-point scale, measuring the extent to which respondents felt (1) anxious and (2) were tense ‘‘these days” (1 – not at all, 2 – slightly, 3 – don't know, 4 – very much 5 –very strongly. Internal reliability was computed as a Pearson correlation (rather than Cronbach's Alpha) because only two items were employed. The reliability was .87, .91, .91, .93, .92, .92 and .92; for the seven assessment waves, respectively.

Virus-specific anxiety was assessed via a single item worded as follows: “To what extent are you worried/stressed by the spread of the Corona Virus”. A seven-point scale was used, where 1 = Not at all and 7 = Very Strongly, but the numbers in between lack a verbal anchor. Notably, single-item measures were shown to be successful in tapping perceived stress and distress during mass-traumas [15].

The following demographic variables were measured: Sex (females vs. males), age (originally continuous, but subsequently transformed into five age groups: 18-30, 30-40, 40-50, 50-60, and 60+), religiosity (transformed into a binary variable, grouping secular and traditional vs. religious and ultraorthodox), education (transformed into having an academic education vs. not), employment (transformed into employed or not), and income (transformed into below average, above average, refused to answer). Income was ultimately not used in the present analyses because of the substantial number of refusals (*n* = 111, 11%).

Data Analysis

All analyses were conducted in Mplus v8.5 **(manufactured by Muthén and Muthén in Los-Angeles, CA, USA),** using the “MLR” estimator. Except as noted, this estimator uses all

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respondents for whom any data were available for the analysis (e.g., even if only one week of anxiety data). ML estimation from raw data accommodates data missing at random. The missing data mechanism is that not every panel member responded to every week's survey. The "robust" maximum likelihood (MLR) estimates use a sandwich estimator for robust standard errors of parameter estimates and, for the single-class models, yield a scaled test statistic.

Data analysis was conducted in the following three phases (with Phase 3 being divided into six steps):

Phase 1: Screening from outliers and careless responding.

This was done via two types of outlier checks: Time to complete survey and Mahalanobis's distance, as well as via a patterned response check (psychological synonyms; see [16], and examples in [17,18]). Checks were applied to the first assessment wave, as subsequent assessment included only three questions each—too few for us to confidently identify outliers or careless responding.

Phase 2: Computation of descriptive statistics.

This was done on the restricted sample resulting from Phase 1. The study variables were characterized using frequencies for binary variables and means, standard deviations, and ranges for the continuous variables. As well, means, standard deviations, and ranges were also calculated for general and virus-specific anxiety across the seven assessment waves. Missing value rates (numbers and proportions) were computed for each variable, and summary statistics were estimated in Mplus with maximum likelihood. [19].

Correlations among the study variables were computed concurrently, enabling future replications and meta-analyses. We also calculated the proportions of respondents meeting a binary criterion for the general anxiety scale. We set the cutoff at >=4 on the 1 to 5 scale, which

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correspond to the "very much" and "very strongly" verbal anchors of the scale. Because the item measuring virus-specific anxiety had anchors only for the extreme scores (i.e., 1 and 7), we did not calculate proportions for this item.

Phase 3: Charting growth trajectories and characterizing them using Wave 0 predictors.

Two outcomes were considered: general and virus-specific anxiety, assessed at the first *post-detection assessment* (Week 1), for the subsequent six assessment waves. Because we anticipated heterogeneous responses to the coronavirus, we estimated latent class growth analyses (LCGAs) and growth mixture models (GMMs) in a structured search, separately for each of the two outcomes.

Analyses were conducted following recommendations by Jung and Wickrama [20]. In addition, we also followed van de Schoot, Sijbrandij, Winter, Depaoli, and Vermunt, [21], who provided guidelines for reporting on latent trajectory studies (i.e., GRoLTS-Checklist). In **Figure 2** we present a flowchart of the various stages employed, linking these stages to Jung and Wickrama [20]. In **Web Table 5** we detail our compliance with the GRoLTS-Checklist.

Stage 1: **Visual inspection.**

Before addressing the Jung and Wickrama's [20] recommendations, we employed a visual inspection of individual trajectory plots. Many plots showed a conspicuous inflection point at the fifth assessment (“Week 4”) for both outcomes, with individual trajectories tending to show a leveling off after increasing to that point.

Given the above-mentioned visual inspection, we based our models on a piecewise functional form, with linear change before and after a spline knot at the fifth assessment.
In all models, growth was modeled as linear from Week 1 through Week 4, then allowed a different linear slope from Week 4 through Week 6. The latent intercept was parameterized as a

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factor with loadings of 1 for each assessment. The first latent slope was parameterized with loadings [-3, -2, -1, 0, 0, 0] and the second slope with loadings [0, 0, 0, 0, 1, 2]. As a result, the model-implied value at Week 4 (when both slope loadings equal 0) is the estimate of the intercept factor. Disturbance variances were independent and constrained to invariance across time within latent class, in order to improve estimability.

***Stage 2:* A latent trajectory model.**

This is done in order to assess whether a parsimonious latent trajectory model fits the data well.

***Stage 3:* LCGAs.**

We employed LCGAs, which impose a within-class homogeneity in the growth factors, namely, the variance-covariance estimates (VCVs) are fixed to zero.

Stage 4: GMMs.

We then employed GMMs, for which the homogeneity of the within-class VCVs is relaxed. Because we hypothesized trajectories near the floor and/or ceiling of the scale, we decided *a priori* to allow the variance-covariance (VCV) matrix of the growth factors to differ between classes, as variances would be expected to be lower the nearer the means are to the scale endpoints. This was then followed by estimating models with the VCV matrices constrained to equality, both to improve estimability and to serve as a sensitivity analysis.

For both LCGAs and GMMs, we used the Mplus command, “STARTS = 1200 200,” which conducts a search for 200 initial best options from 1,200 random sets of starting values, then attempts to estimate the resulting 200 models. For all models reported as stable across starting values, at least 5 of those 200 converged on the same solution and the replicated solution had the lowest log-likelihood of the 200.

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Stage 5: **Determination of the final model.**

Then, we used fit indices to decide on the final model. For the single class, latent trajectory model, the conventional fit indices – RMSEA, CFI, TLI – were used. For the LCGAs and GMMs, we used the Lo-Mendell-Rubin test (LMR) and the bootstrapped likelihood ratio test (bLRT) to assess the appropriate number of classes within each model type (e.g., LCGA, GMM). For these tests, the default settings for numbers of starting values can be insufficient. Where these settings did not yield a solution, we report the test as inestimable. Following recommendations by van de Schoot et al. [21], we relied on the Sample-size Adjusted Bayesian Information Criterion (SABIC) to compare fit between types of models.

Stage 6: Prediction of class membership.

We predicted class membership via respondent age (grouped), gender, religiosity (binary), and education (binary: degree completed), as well as both general and virus-specific anxiety from the first assessment. Employment was not entered into this analysis because there was little variability: 92% were employed. Prediction was tested using the 3-step method incorporated into the R3STEP option in M*plus.* This procedure automates the prediction of individual class membership based on the original mixture models incorporating individual-level uncertainty in class assignment [22]. We computed odds ratios and confidence intervals for the effect of each predictor in the multiple multinomial regression on likelihood of membership in each class, contrasted pairwise with every other class. Because this pairwise examination resulted in more contrasts than degrees of freedom, we applied Holm's family-wise error rate correction, separately for each predictor [23]. The R3STEP function applies listwise deletion based on the predictors. Finally, we applied the "BCH" method in Mplus to estimate descriptive values of the covariates within each class.

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RESULTS

Phase 1: Screening from outliers and careless responding.

Our first assessment of careless responding was to examine the time taken to complete the assessment for left-side (i.e., suspiciously brief) outliers. Visual inspection of plotted completion times indicated none.

Our second assessment of careless responding was a psychometric synonyms measure, following Meade & Craig (2012; our instrument did not lend itself to the recommended, complementary, psychometric antonyms assessment, Goldberg, 2000, cited in Meade & Craig, 2012). We estimated correlations among the 17 subjective items (including items not used in this paper, but still relevant to response patterns) in the first assessment, for 136 pairwise correlation coefficients. Eight of those correlations exceeded .60. We then estimated within-respondent correlations across $n = 8$ pairs, treating the pairs as interchangeable, following the logic that within-respondent correlations should generally be positive for items where between-respondent correlations are high. We used a cutoff of within-respondent $r <= -.52$. Given $n = 8$, the 95% confidence interval for that correlation excludes positive values great than .30. Fifteen respondents (1.5%) fell below this threshold and were excluded from primary analyses.

The third, complementary, strategy for screening was to check for multivariate outliers in the first assessment. We used the 15 subjective continuous items, again including additional items for screening purposes, and calculated Mahalanobis's distances from the centroid. The distances were plotted versus a chi-squared distribution with 15 degrees of freedom. Thirteen (13, 1.3%) observations were significantly above the midline of the Q-Q plot, $p < .001$, and were excluded from primary analyses.

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In total, 27 (2.7%) of the 1,018 respondents were screened out of the sample following these procedures: 14 for careless responding, 12 as multivariate outliers, and one who met both criteria. All results below are based on the remaining sample of 991 participants.

Phase 2: Descriptive Statistics.

In **Web Table 6** we present the intercorrelations among the study variables.

In **Tables 1 and 2** we present descriptive statistics of the demographic and anxiety variables (continuous and binary variables, respectively). It is noteworthy that baseline (pre-detection) levels of general anxiety in this study (M = 2.14, SD = 1.06) are almost identical to those reported in a previous study on Jewish-Israeli adults assessed prior, and subsequent, to a military crisis[5] (namely, 2.29[1.07] and 2.21[1.01], respectively. In both studies, the very same sampling procedure and assessment of general anxiety were used, lending additional support for the representativeness of the present sample.

For clarity of presentation, means of the two outcomes across time are plotted in **Figures 3 and 4.** This enables the reader to understand why we examined trajectory models that allow for a plateau transpiring after weeks of a linear growth. As shown in the figure, the plateau started at Week 4 (i.e., the 5th assessment).

Strongly corresponding to the above pattern is our findings from calculating proportions of general anxiety (scores >4), which were 13.5%, 18.4%, 23.4%, 33.5%, 46.2%, 43.7%, and 42.6%, for weeks 0-6, respectively.

Phase 3: Growth Trajectories and their prediction.

General Anxiety.

Stages 1 and 2: **Visual inspection and a single-class latent trajectory model.**

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As noted above, visual inspection identified a knot (spline) at Week 5. The estimated models and their relative fit are summarized in **Table 3.** The single-class latent trajectory model fit the data adequately by common criteria for approximate fit measures, est. RMSEA = .072, 95% CI [.059, .086], CFI = .974, TLI = .977, SRMR - .063, ($\chi 2_{[17, N = 960]}$ = 100.95, p < .001). However, the RMSEA estimate and its lower confidence bound were both higher than common standards for "close fit" (.050; e.g., [24]),

Stages 3 and 4 (LCGAs and GMMs).

In **Table 3,** we also present the LGCAs and GMMs that were tested. For reasons of clarity and brevity, we relegate the description of each of the model specification and fit to **Web Appendix 2.** By way of a summary, we note that two LCGAs were examined (with 2 and 3 classes, respectively), and the more parsimonious 2-class model was preferred to the 3-class model. As well, four GMMs were examined, and the GMM fitting best was a 4-class model, which was preferred over the 2-class LCGA based on the fit indices.

Stage 5: Characteristics of the final model.

Characteristics of the 4-classes model are presented in **Tables 4 and 5.** The mean trajectories within each class, along with full-sample means, are shown in **Figure 4.** Correlations between the change factors are presented in **Table 5.**

In this model, our three hypothesized classes emerged: A threat-sensitive class estimated at 29% of the population starts low, showing an increase (0.66 per week, SE = 0.03, z = 19.78, p < .001) to a relatively high level at Week 4 (4.10 on scale of 1 to 5), and a leveling off after (-.01 per week, SE = 0.04, z = -0.13, p =.897).

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A complacency class, estimated as 29% of the population, starts low, showing a shallow increase (0.09 per week, *SE* = 0.01, *z* = 7.29, *p* < .001) to a still-low level at Week 4 (1.82), then leveling off (0.00 per week, *SE* = 0.02, *z* = -0.09, *p* = .931).

Then, a panic class, estimated as 12% of the population, starts high (4.14), showing an increase (0.14 per week, *SE* = 0.02, *z* = 6.00, *p* < .001) to a near-ceiling level at Week 4 (4.56), then a leveling off (-0.04 per week, *SE* = 0.02, *z* = -1.41, *p* = .160).

The fourth, not hypothesized, class estimated 30% of the population, was characterized by medium and quite stable levels of general anxiety, starting slightly below the mid-level, then evincing a very shallow increase (0.20 per week, *SE* = 0.05, *z* = 4.40, *p* < .001) till Week 4 (2.84), then leveling off (.01 per week, *SE* = 0.05, *z* = 0.18, *p* = .861). Because the literature suggests that too little and too high anxiety are detrimental, we title this class "Balanced" (see **Table 4**).

Stage 6: Class predictions.

Detailed results of the R3STEP prediction of class membership are shown in **Web Table 7.** Listwise deletion resulted in *N* = 958 for this analysis.

Older respondents were more likely to be in the complacency class than the balanced class, *OR* (per step in age) = 1.27, 95% CI [1.07, 1.50]. Male respondents were more likely than female respondents to be in the complacency class than the panic class, *OR* = 5.86 [2.74, 12.51], and similarly less likely to be in the panic class than in the balanced class, *OR* = 0.23 [0.11, 0.48]. The inverse pattern applies to women, i.e., the were more likely to be in the panic class than in the complacency and balance classes. They were also more likely than men to belong to the panic class than the threat-sensitivity class.

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Baseline general anxiety was associated with higher likelihood of membership in the panic class than any of the other three and lower likelihood of membership in the complacency class than any other class, though not discriminating significantly between the balanced and threat-sensitive classes.

Baseline virus-specific anxiety predicted a lower likelihood of membership in the complacency class compared to the panic or threat-sensitive classes and greater likelihood of membership in the panic class than the balanced class. As well, baseline virus-specific anxiety also predicted increased likelihood of membership in the threat-sensitive class relative to the balanced class.

Estimated descriptive statistics from the BCH method for the covariates within class are shown in the right-hand panel of **Web Table 7.**

Virus-Specific Anxiety.

Stages 1 and 2: Visual inspection and a single class latent trajectory model.

Again, the visual inspection identified a knot, or a spline, at Week 5. The estimated models and their relative fit are summarized in **Table 6.**

The single-class model fit the data adequately by approximate measures, est. RMSEA = .073, 95% CI [.060, .087], CFI = .97, TLI = .97, SRMR = .07 ($\chi 2_{[17, N = 958]} = 104.64$, $p < .001$), but not "closely" by RMSEA and its confidence interval.

Stages 3 and 4: LCGAs and GMMs.

In **Table 6,** we also present the LGCAs and GMMs that were tested. An elaborated description of these models appears in **Web Appendix 2**). To summarize, 2-and-3 classes LCGAs were examined, and fit indices identified the 3-class LCGA was preferred. As well, three

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GMMs were examined, culminating in a 3-class, equated variance-covariance as the best fitting model.

Stage 5: Characteristics of the final model.

Characteristics of the final model are presented in **Tables 7 and 8.** The mean trajectories within each class, along with full-sample means, are shown in **Figure 7** In this solution, a class estimated at 66% of the population showed an increase (0.48 per week, $SE = 0.03$, $z = 17.31$, $p < .001$) to a moderate level at Week 4 (4.82 on scale of 1 to 7), and a leveling off after (0.00 per week, $SE = 0.03$, $z = -0.06$, $p = .954$). This is consistent with the threat-sensitive hypothesis.

The second class, estimated as 9% of the population, showed a shallow increase (0.13 per week, $SE = 0.05$, $z = 2.75$, $p = .006$) to a still-low level at Week 4 (2.35), then a leveling (-0.02 per week, $SE = 0.08$, $z = -0.35$, $p = .727$), consistent with the complacency hypothesis.

The third class, estimated as 25% of the population, showed an increase (0.24 per week, $SE = 0.05$, $z = 5.14$, $p < .001$) to a near-ceiling level at Week 4 (6.23), then a leveling off (-0.05 per week, $SE = 0.03$, $z = -1.86$, $p = .063$). The model-implied values for this class at Week 1 was an already high 5.51, conforming to the panic hypothesis.

Stage 6: Class prediction.

Detailed results of the R3STEP prediction of class membership are shown in **Table 9**. Listwise deletion resulted in $N = 956$ for this analysis.

As expected, higher baseline virus-specific anxiety clearly predicted class membership. Respondents with higher baseline virus-specific anxiety were more likely to be in panic class than either the threat-sensitive class, *OR* per scale point = 2.31, 95% CI [1.88, 2.84[, or the complacency class, *OR* = 5.11 [3.41, 7.64] Baseline virus-specific anxiety also predicted membership in the threat-sensitive class over the complacency class, *OR* = 2.21 [1.55, 3.16[

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Baseline general anxiety did not significantly predict class membership after the Holm correction.

The BCH procedure to estimate descriptive statistics within class failed, with Mplus reporting an error in computations. After multiple attempts to resolve the error, we concluded the problem was likely to be related to the zero-constrained variance.

DISCUSSION

When the World Health Organization (WHO) director general stated that COVID-19 is a pandemic, he added that pandemic is not a word used lightly: if misused, it can cause unreasonable fear [3]. Indeed, attempts of local governments to mitigate outbreaks by imposing fear might have the unintended consequence of overwhelming the social and economic fabric of society, as well as to contribute to the continuous stress incurred by the spread [25]. However, as is consensually accepted, COVID-19 is indeed a pandemic, and it has been delivering a devastating blow to individuals' health (both mental and physical), economies, and societies worldwide.

Herein we report on findings from a longitudinal assessment of general and virus-specific anxiety experienced by Jewish-Israeli adults during the 1st wave of the spread of COVID-19, encompassing a six-week period. Our baseline assessment took place *before* the first appearance of a "case" in the country of Israel. Even then, anticipation was building up in the population between Dec 31, 2019, when the Chinese city of Wuhan reported an outbreak of atypical pneumonia [26], and January 27th 2020, when the European Centre for Disease Prevention and Control (ECDC) and the WHO Regional Office for Europe asked countries to complete a WHO standard COVID-19 case report form for all confirmed and probable cases that met WHO criteria [27]. While the Israeli Ministry of Health (MoH) employed strict measures at very early stages, resulting in a modest spread of the disease, the press -- and several politicians -- were very

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intensively discussing horrendous scenarios. This was likely to increase the populations anxiety, given studies showing that the media can bias our perceptions of disease [28,29]. Documenting the unfolding of general anxiety, as well as specific anxiety concerning the virus, was therefore essential.

For both general and virus-specific anxiety, our hypothesized three classes emerged: (1) a threat-sensitive class evincing a linear increase till Week 4, then plateauing (29% and 66%, for each outcome, respectively), (2) a complacency model, characterized by low (general and virus-specific) anxiety slightly increasing over the study period (29% and 9%, respectively), and (3) a third, panic class starting very high and increasing in a linear fashion close to the ceiling (12% and 25%, respectively). In addition, for general anxiety, a non-hypothesized, albeit large (30%) and highly intriguing, fourth class emerged, evincing stable, mid-levels of general anxiety throughout the study period. We now discuss the implications of each of these classes in turn.

The two extreme classes in each outcome – low and high anxiety -- can be said to reflect the hypothesized complacency and panic trajectories. As for the low anxiety class, although it did not pertain to a straight line, the linear increase in this class was so modest (and culminating in a low anxiety level at the last wave) to be deemed as reflecting complacency: Despite the apparent threat, 29% of our sample were unperturbed in terms of general anxiety, and 9% were not worried about the spread of the virus. As shown in previous research [10,11], complacency can be identifiable at times of medical crises, and it can be quite harmful.

As for the high-anxiety class, it is consistent with a "panic" trajectory where levels of anxiety are high already for the start and are even increasing with time [9]. This interpretation, however, should be tempered given the possibility that a subset of the population (12% and 25%, for each outcome, respectively), may constantly suffer from high anxiety regardless of the

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circumstances. That this class is relatively small may explain previous research reporting the absence of panic at times of disasters and large-scale political crises[30] , in that these studies did not allow for the possibility of various classes of trajectories included in the their sample. In subsequent analyses, we are examining the public and mental health consequences of already belonging to the high-anxiety class.

For both outcomes, a large class was consistent with the *threat-sensitive model*, according to which levels of general and virus-specific anxiety start normatively low, but increase in a linear fashion as the threat grows, and then plateauing. We construe this plateau as reflecting *habituation.* As described in the landmark paper by Thompson and Spencer [31], habituation is a form of simple, nonassociative learning in which the magnitude of the response to a specific stimulus decreases with repeated exposure to that stimulus. It has been known for several decades that the magnitude of hypothalamic-pituitary-adrenal activation occurring in response to a stressor declines with repeated exposure to that same stressor, and this decline has been referred to as "habituation" in the stress neurobiology literature [32].

When general, but not virus-specific, anxiety was considered as the outcome, we also identified a non-hypothesized, large (30%), fourth class, in which mid-levels of general anxiety were evinced from the outset, remaining stable across the six assessments. We title this class "balanced" in order to distinguish it from the detrimental panic and complacency trajectories, and even from the threat-sensitivity class which, while starting mid-level, ascended in terms of general anxiety until it reached a plateau. Consistent with our interpretation of this trajectory as largely adaptive, we found that baseline virus-specific anxiety distinguished this trajectory with the trajectory to which it is closest, namely, the threat-sensitive trajectory: Lower levels of virus-specific anxiety were evinced for the balanced trajectory. Unfortunately, this was the only

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predictor uniquely characterizing the balanced trajectory. We intend to further characterize this trajectory by (1) examining its relevance to variables assessed subsequent to the 1st level of the spread, (2) testing prediction of this trajectory by other variables assessed at baseline, but which are not reported here (e.g., attitudes towards the Ministry of Health), and (3) conducting qualitative interviews with a representative sample of members of this class.

Week 0 predictors of the various classes for each outcome were informative. Interestingly, while both general and virus-specific anxiety predicted – in expected ways – membership in the general anxiety classes, only virus-specific anxiety predicted membership in the virus-specific anxiety classes. Indeed, in developing the assessment protocol, we were explicitly influenced by literature on perceived stress [15], whereby virus-specific anxiety is "a risk factor" for general anxiety symptoms. Nevertheless, we also allowed for a reverse, or bi-relational/cross-lagged prospective association, because these prospective associations are often observed in psychopathology [33]. Our actual findings are consistent with the construal of virus-specific anxiety as the stressor, and with general anxiety as the stress-reactive outcome. This pattern is important because it suggests that some of the changes in general anxiety are attributable to anxiety about COVID-19.

Second, gender markedly distinguished between participants membership in the classes pertaining to general, but not virus-specific anxiety: Women were decidedly more anxious than men, and their anxiety was more likely to place the in the panic class (and men's – in the complacency class). However, because such associations were found only for general anxiety, it is possible that these gender differences, well documented in previous research, are unrelated to the COVID-19 crisis.

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Third, older participants were more likely to belong to a general (but not virus-specific) *low anxiety* (i.e. complacency) class. Overall, the moderating role of age has been documented in previous research , concerning mass disasters [34]. We are not sure why older participants in our sample reported levels of anxiety that were that low, and whether such low-end anxiety does indeed reflect complacency.

Implications for public health interventions are noteworthy. That a large subset of this sample was threat-sensitive in terms of both general and virus-specific anxiety suggests that this particular public may be an intense consumer of data regarding the spread, the infected, and the deceased. To the extent that this post-hoc speculation is correct, quantitative information provided by medical leadership, as opposed to dramatic declarations, should be at the forefront of messages to the public. Relatedly, that baseline levels of virus-specific anxiety predicted – in the expected direction -- subsequent membership in the general anxiety trajectory, highlight the need to assess anxiety that is specific to the unfolding medical crises at the earliest stages of such crises. As for the identification of the "balanced", general anxiety class, and the predictive associations involving gender and age, we refrain from pointing out public health implications until we ascertain that this class, and such predictive associations, are specific to the COVID-19 crisis.

Study's strengths vs. limitations should be noted. The most important strength is our assessment of the variables of interest prior to the entry of o COVID-19 to Israel, enabling us to use a strong baseline as an anchor point. Second, the utilization of seven weekly assessments enabled a relatively precise charting of those changes over time. Third, differentiating between general and virus-specific anxiety allowed for attaining a fine-grained appreciation of the unfolding of anxiety in the Jewish-Israeli public. Limitations include an employment of brief,

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self-report measures (but the use of extensive clinical batteries might have overwhelmed participants, increasing attrition), an online recruitment procedure (the only way to recruit under the circumstances), and the focus on a solely Jewish sample (however, we are currently collecting data from Israeli Arabs).

Even now (July, 2021), despite the recent introduction of effective vaccines as the first-line measure for managing the pandemic, variants of COVID-19 still challenge the public and its behavior, and behavioral measures are still considered a paramount in influencing levels of the spreads. We hope that our findings charting the unfolding of anxiety in the face of the pandemic would be useful to policy makers and public health experts -- inside and beyond Israel -- in stirring public behavior toward responsible, compliant routes.

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Table 1: Sample demographics, Non-binary variables.
(Israeli Public Behavior Project; Beer-Sheva, Israel, 2019).

Variable	M(SD)	Range	Skewness	Kurtosis	N	(%MVs)
Age	42.69 (15.66)	18-74	0.25	-1.08	991	0
Age groups	2.80 (1.44)	1-5	0.21	-1.31	991	0
GA Week 0	2.14 (1.06)	1-5	1.03	0.31	991	0
VSA Week 0	3.68 (1.84)	1-7	0.19	-0.99	985	1
GA Week 1	2.30 (1.09)	1-5	0.83	-0.21	852	14
VSA Week 1	3.86 (1.70)	1-7	0.10	-0.89	849	14
GA Week 2	2.47 (1.14)	1-5	0.59	-0.73	800	19
VSA Week 2	4.11 (1.78)	1-7	-0.07	-0.94	799	19
GA Week 3	2.80 (1.22)	1-5	0.30	-1.13	796	20
VSA Week 3	4.53 (1.77)	1-7	-0.28	-0.89	795	20
GA Week 4	3.17 (1.23)	1-5	-0.03	-1.33	767	23
VSA Week 4	5.00 (1.66)	1-7	-0.53	-0.58	764	23
GA Week 5	3.17 (1.25)	1-5	-0.03	-1.28	769	22
VSA Week 5	5.05 (1.67)	1-7	-0.59	-0.48	769	22
GA Week 6	3.11 (1.24)	1-5	0.00	-1.27	735	74
VSA Week 6	4.91 (1.67)	1-7	-0.50	-0.63	735	74

Abbreviations:
M = Means; SD = Standard Deviations; N = Sample size; MVs = Missing Values; GA = General Anxiety; VSA = Virus Specific Anxiety.

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Table 2: Sample demographics, binary variables.
(Israeli Public Behavior Project; Beer-Sheva, Israel, 2019).

Variable	No.	%	**N**	**(%MVs)**
Gender			991	0
Women	508	51		
Men	483	49		
Religion			991	0
Religious	235	24		
Secular	7863	76		
Education			989	<1
Academic	660	67		
Non-Academic	329	33		
Employment status			991	0
Employed	916	92		
Unemployed	75	8		
Income[a]			952	6
Below or Average	762	82		
Above Average	165	18		

Abbreviations:
MVs = Missing Values
[a] 64 participants (6%) refused to respond to the income item. [a]

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Table 3. Fit statistics for all estimated general anxiety models.
(Israeli Public Behavior Project; Beer-Sheva, Israel, 2019).

Model	SABIC	LMR vs. 1 fewer classes	p	bLRT (df) vs. 1 fewer classes	p	χ^2 (df)	p	RMSEA	RMSEA CI	CFI	TLI	SRMR
1 class	11880					100.95 (17)	<.001	.072	.059,.086	0.974	0.977	0.063
LCGA 2-class	12537	2493.71	<.001	2566.34 (5)	<.001	[a]	[a]	[a]	[a]	[a]	[a]	[a]
GMM 2-class / free VCV	11119	790.85	<.001	Inest. [b]	[a]	[a]	[a]	[a]	[a]	[a]	[a]	[a]
GMM 3-class / free VCV [c]	11034	123.75	0.052	Inest. [b]	[a]	[a]	[a]	[a]	[a]	[a]	[a]	[a]
GMM 2-class / equated VCV [d]	Inest. [b]	Inest. [b]		Inest. [b]	[a]	[a]	[a]	[a]	[a]	[a]	[a]	[a]
GMM 3-class / equated VCV	10901	Inest. [b]		Inest. [b]	[a]	[a]	[a]	[a]	[a]	[a]	[a]	[a]
GMM 4-class / equated VCV [e]	10774	141.28	<.001	145.39 (5)	<.001	[a]	[a]	[a]	[a]	[a]	[a]	[a]

Abbreviations:
LCGA: latent class growth analyses; GMM: growth mixture models; VCV: Variance-Covariance; SABIC = is sample-size-adjusted Bayesian Information Criterion; LMR: Lo-Mendell-Rubin test; bLRT: Bootstrapped Likelihood Ratio Test; CFI: Confirmatory Fit Index; TLI: Tucker-Lewis Index; RMSEA: Root Mean Square Error of Approximation; CI = Confidence Intervals; SPMR: Standardized Root Mean Square Residual.

[a] Statistic not available for model.
[b] Inest." Indicates statistic empirically inestimable for model.
[c] Improper solution
[d] No stable solution
[e] Final model.

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Table 4. Parameter estimates of the final general anxiety model. (Israeli Public Behavior Project; Beer-Sheva, Israel, 2019). [a b c d]

Class Label	Proportion of Population	Slope (Standard Error) Week 1 to Week 4	Week 4 Implied Mean (Standard Error)	Slope (Standard Error) Week 4 to Week 6
Balanced	.30	0.20 (0.05) [e]	2.84 (0.13)	0.01 (0.05)
Complacency	.29	0.09 (0.01) [e]	1.82 (0.03)	0.00 (0.02)
Threat-Sensitive	.29	0.66 (0.03) [e]	4.10 (0.08)	-0.01 (0.04)
Panic	.12	0.14 (0.02) [e]	4.56 (0.06)	-0.04 (0.02)

Abbreviations:
[a] Tabled values are in original metric (1-5).
[b] Upper panel shows point estimates of trajectory parameters by class.
[c] Slopes are per week.
[d] Significance not evaluated for means as floor of scale is greater than zero.
[e] $p < .001$

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Table 5. Correlations among estimates of the final general anxiety model Correlations (Standard Deviations on Diagonal).
(Israeli Public Behavior Project; Beer-Sheva, Israel, 2019).

Slope Week 1 to Week 4	0.11		
Week 4 Mean	0.20	0.42	
Slope Week 4 to Week 6	0.57	-0.04	0.05

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Table 6. Fit statistics for all estimated virus-specific anxiety models. (Israeli Public Behavior Project; Beer-Sheva, Israel, 2019).

Model	SABIC	LMR vs. 1 fewer classes	p	bLRT (df) vs. 1 fewer classes	p	χ^2 (df)	p	RMSEA	RMSEA CI	CFI	TLI	SRMR
1 class	15045					104.64 (17)	<.001	.073	(.060, .087)	0.97	0.97	0.07
LCGA 2-class	16145	2260.30	<.001	2326.15 (5)	<.001	[a]	[a]	[a]	[a]	[a]	[a]	[a]
LCGA 3-class	15228	909.36	<.001	935.86 (5)	<.001	[a]	[a]	[a]	[a]	[a]	[a]	[a]
GMM 2-class / free VCV [c]	14434	641.10	0.212	Inest. [b]	[a]	[a]	[a]	[a]	[a]	[a]	[a]	[a]
GMM 3-class / equated VCV [c]	14382	Inest. [b]		Inest. [b]	[a]	[a]	[a]	[a]	[a]	[a]	[a]	[a]
GMM 3-class / equated VCV with constrained Heywood case [e]	14497	118.75	0.013	123.08 (4)	<.001	[a]	[a]	[a]	[a]	[a]	[a]	[a]

Abbreviations:

LCGA: latent class growth analyses; GMM: growth mixture models; VCV: Variance-Covariance; SABIC = is sample-size-adjusted Bayesian Information Criterion; LMR: Lo-Mendell-Rubin test; bLRT: Bootstrapped Likelihood Ratio Test; CFI: Confirmatory Fit Index; TLI: Tucker-Lewis Index; RMSEA: Root Mean Square Error of Approximation; CI = Confidence Intervals; SPMR: Standardized Root Mean Square Residual.

[a] Empty cell indicates statistic not available for model.

[b] "Inest." Indicates statistic empirically inestimable for model.

[c] Improper solution

[d] Final model.

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Table 7. Parameter estimates of the final virus-specific anxiety model. (Israeli Public Behavior Project; Beer-Sheva, Israel, 2019). [a b c d e]

Class Label	Proportion of Population	Slope (Standard Error) Week 1 to Week 4	Week 4 Implied Mean (Standard Error)	Slope (Standard Error) Week 4 to Week 6
Complacency	.09	0.13 (0.05) [f]	2.35 (0.13)	-0.02 (0.08)
Threat-Sensitive	.66	0.48 (0.03) [g]	4.82 (0.07)	0.00 (0.03)
Panic	.25	0.24 (0.05) [g]	6.23 (0.08)	-0.05 (0.03)

Abbreviations:
[a] Tabled values are in original metric (1-7).
[b] Upper panel shows point estimates of trajectory parameters by class.
[c] Slopes are per week.
[d] Significance not evaluated for means as floor of scale is greater than zero.
[e] Lower panel shows standard deviations and correlations of trajectory parameters (equated across class).
[f] $p < .01$;
[g] $p < .001$

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Table 8: Correlations among estimates of the final virus-specific anxiety model Correlations (Standard Deviations on Diagonal).
(Israeli Public Behavior Project; Beer-Sheva, Israel, 2019).

Slope Week 1 to Week 4	0.27		
Week 4 Mean	0.36	1.06	
Slope Week 4 to Week 6	[a]	[a]	[a]

[a] Variance and covariances of Slope Week 4 to Week 6 constrained to zero.

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Table 9. Logistic Regression Results Predicting Virus-Specific Anxiety Trajectory Class (Israeli Public Behavior Project; Beer-Sheva, Israel, 2019).

Predictor	Odds Ratios (95% Confidence Intervals)					
	Panic vs. Threat-Sensitive		Panic vs. Complacency		Threat-Sensitive vs. Complacency	
	OR	95% CI	OR	95% CI	OR	95% CI
Age Groups	0.92	0.77, 1.10	0.87	0.66, 1.15	0.94	0.75, 1.19
Religious (binary)	0.76	0.37, 1.57	0.84	0.31, 2.28	1.11	0.53, 2.32
College (binary)	1.51	0.87, 2.62	1.12	0.44, 2.86	0.75	0.34, 1.64
Gender (male coded high)	0.92	0.54, 1.53	0.57	0.25, 1.31	0.62	0.31, 1.24
Week 0 General anxiety (5-point scale)	1.24	0.95, 1.62	2.25	1.03, 4.90	1.81	0.85, 3.82
Week 0 Virus-specific anxiety (7-point	2.31 [c]	1.88, 2.84	5.11 [c]	3.41, 7.64	2.21 [c c]	1.55, 3.16

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scale)						

[a] Tabled odds ratios for each pairwise comparison (reference groups noted in column headers) are per unit increase in original metric, as noted.
[b] The null hypothesis of no unique prediction corresponds to an odds ratio of one.
[c] Statistically significant odds ratios after Familywise Error Rate adjustment within row.

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Figure 1: RECRUITMENT FLOWCHART. (Israeli Public Behavior Project; Beer-Sheva, Israel, 2019). The graph shows the recruitment procedure employed by the MIDGAM panel. Each box represents a recruitment stage, alongside the putative sample size (n) enabled by this stage. "Wave" pertains to the pertinent assessment wave.

Abbreviation: n = sample size.

Figure 2: A FLOWCHART SUMMARIZING THE TRAJECTORTY ANALYSES. (Israeli Public Behavior Project; Beer-Sheva, Israel, 2019).

Abbreviations: LTA = Latent Trajectory Analysis; RMSEA: Root Mean Square Error of Approximation; CFI: Confirmatory Fit Index; TLI: Tucker-Lewis Index; LCGA: latent class growth analyses; GMM: growth mixture models; SABIC = is sample-size-adjusted Bayesian Information Criterion; LMR: Lo-Mendell-Rubin test; bLRT: Bootstrapped Likelihood Ratio Test.

This graph shows the various stages employed in the course of the complex data analytic process utilized for this study. As detailed in the text, the various stages integrates various statistical tasks, namely, data cleaning and management, preparing for modeling, numerous modeling procedures, completion of modeling checklists.

Figure 3: GENERAL ANXIETY OVER TIME. (Israeli Public Behavior Project; Beer-Sheva, Israel, 2019).

This graph depicts the mean levels of general anxiety across the seven assessment waves. X axis pertain to the assessment waves (waves 0-6), whereas Y axis refers to the measurement scale (1-5).

Figure 4: VIRUS-SPECIFIC ANXIETY OVER TIME. (Israeli Public Behavior Project; Beer-Sheva, Israel, 2019).

This graph depicts the mean levels of virus-specific anxiety across the seven assessment waves. X axis pertain to the assessment waves (waves 0-6), whereas Y axis refers to the measurement scale (1-7).

Figure 5: GENERAL ANXIETY TRAJECTORIES. (Israeli Public Behavior Project; Beer-Sheva, Israel, 2019).

This graph shows the various classes, or trajectories, identified for general anxiety. X axis pertains to the assessment waves (waves 1-6). Y axis refers to the measurement scale (1-5). The lines in colors represent the various classes, or trajectories. The navy-blue line represents the "panic" class. The yellow line pertains to the "threat-sensitivity" class. The light blue class represents the raw data (as in Figure 3). The gray line corresponds to the "balanced" class. Finally, the orange line pertains to the "complacency" class. The box within the graph depicts the sample percentages of members belonging to the various classes.

Figure 6: VIRUS-SPECIFIC ANXIETY TRAJECTORIES.

This graph shows the various classes, or trajectories, identified for virus-specific anxiety. X axis pertains to the assessment waves (waves 1-6). Y axis refers to the measurement scale (1-7). The lines in colors represent the various classes, or trajectories. The yellow line represents the "panic" class. The light blue class represents the raw data (as in Figure 5). The gray line pertains to the "threat-sensitivity" class. The orange line represents the 'complacency" class. The box within the graph depicts the sample percentages of members belonging to the various classes.

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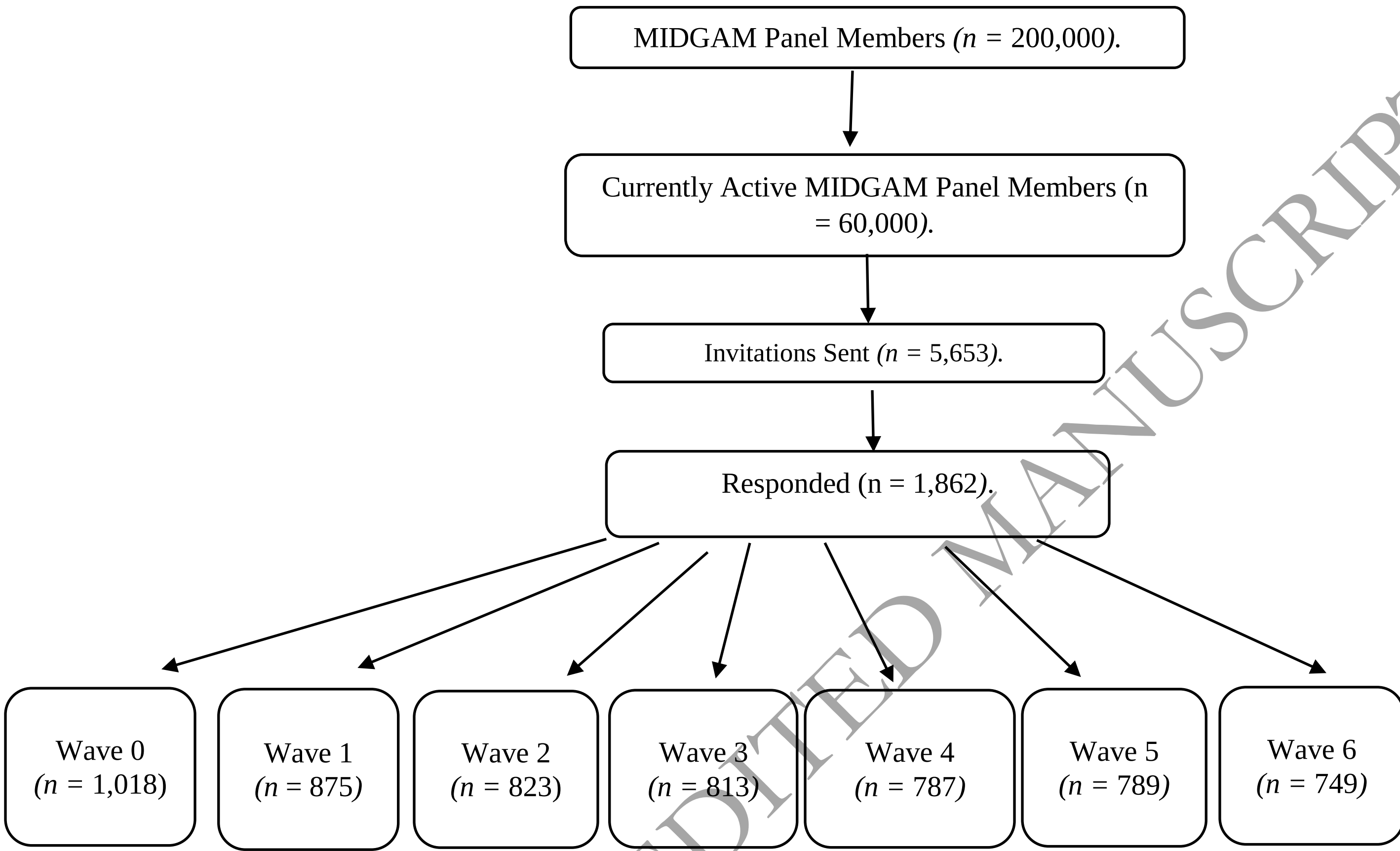

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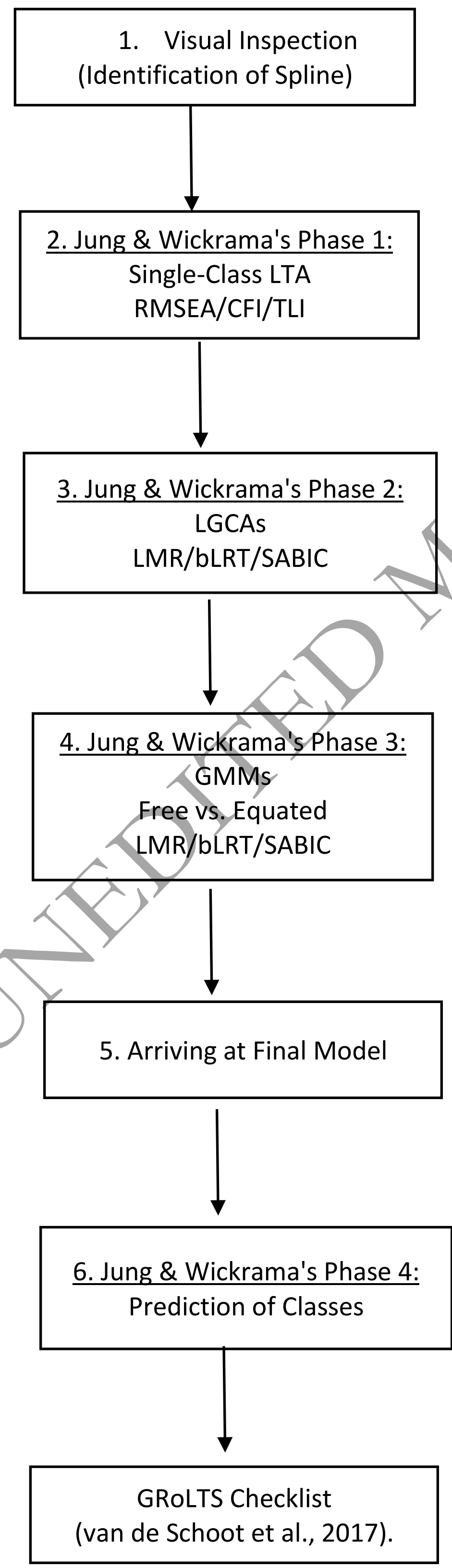

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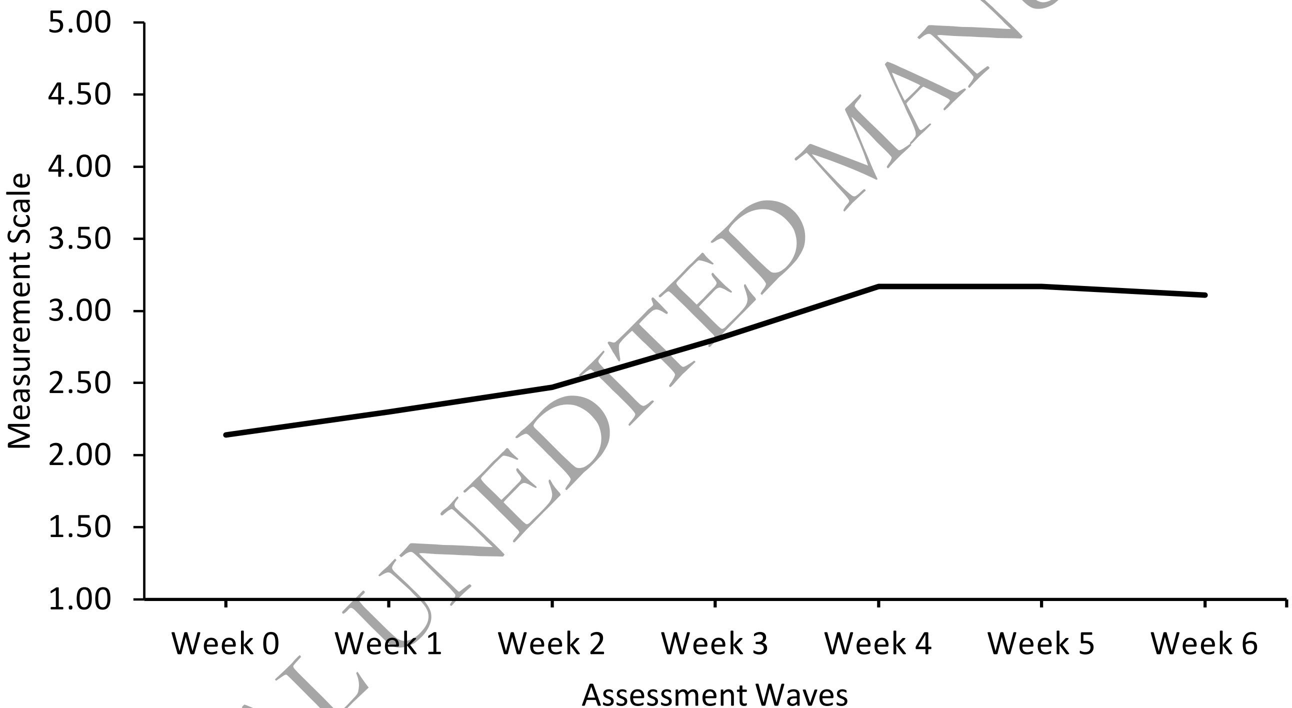

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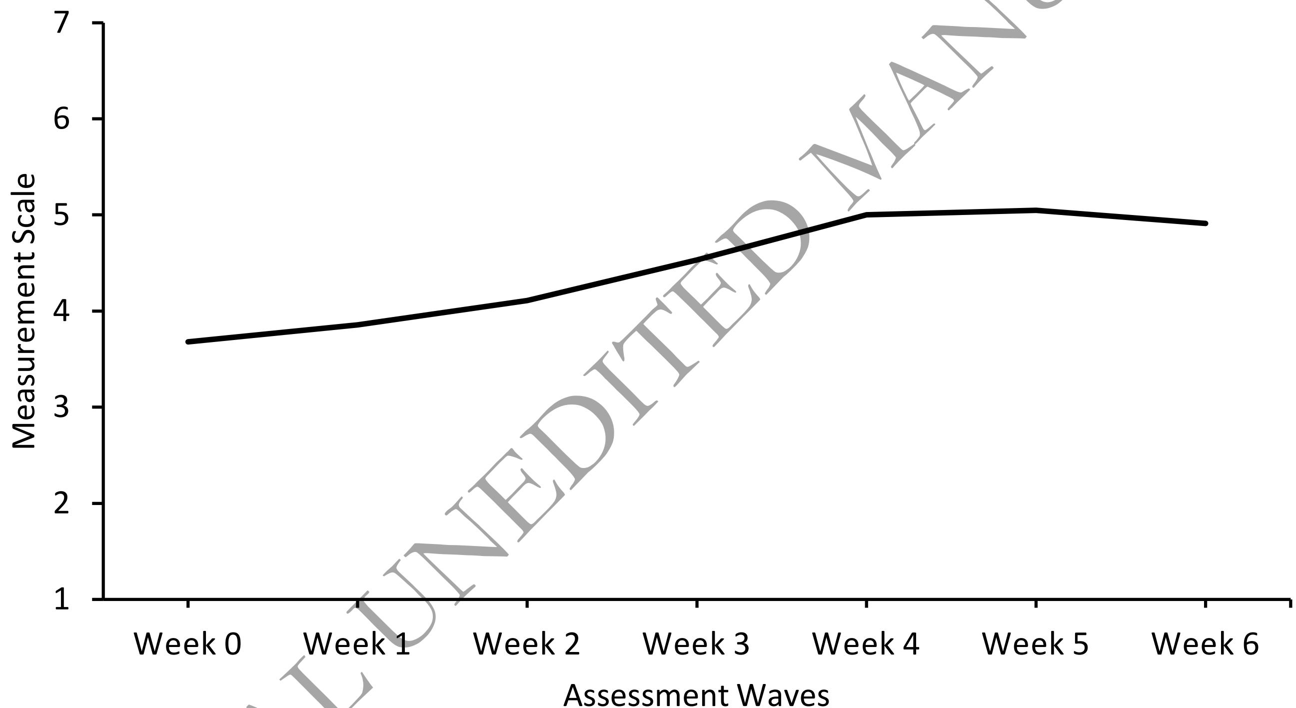

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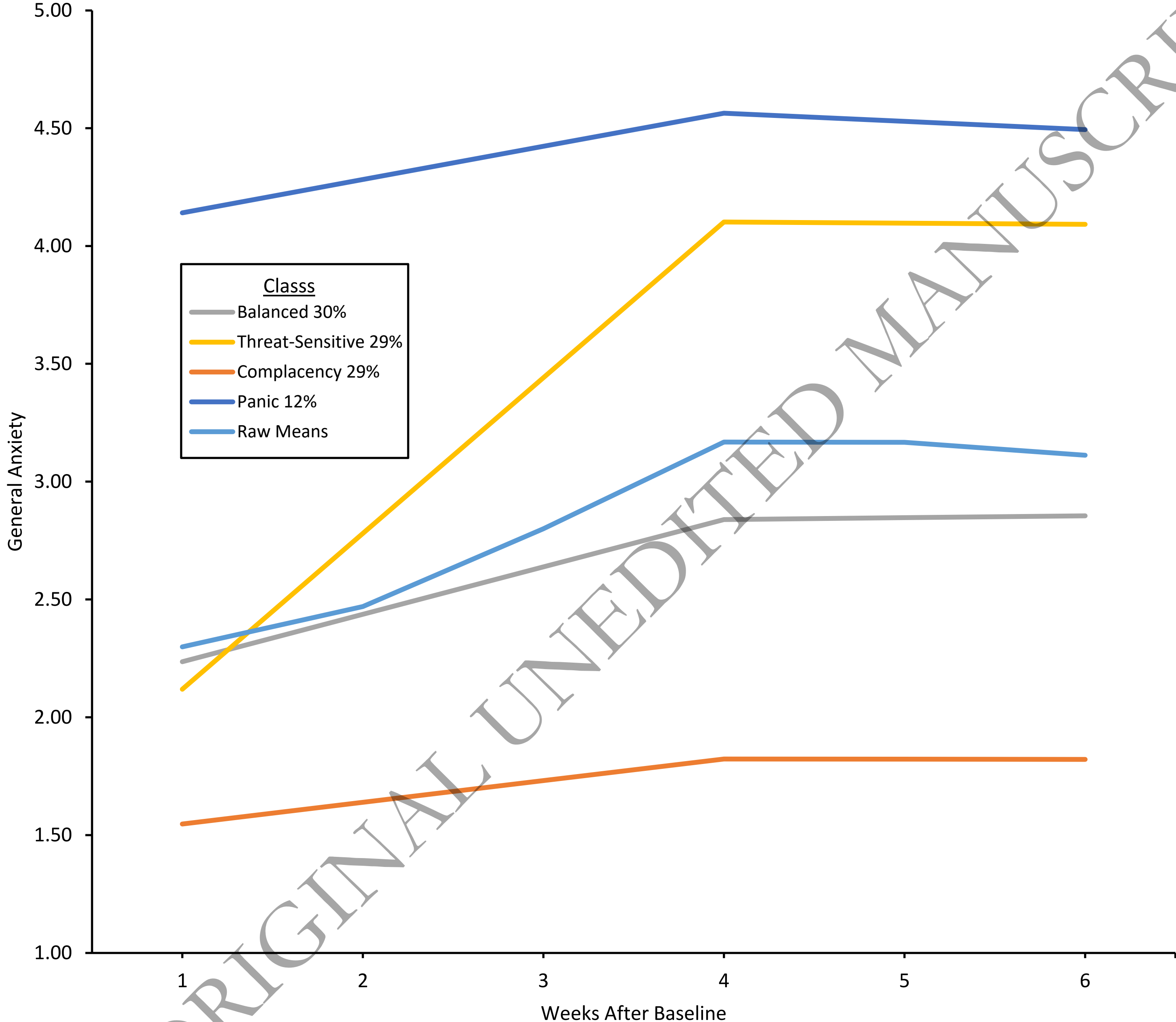

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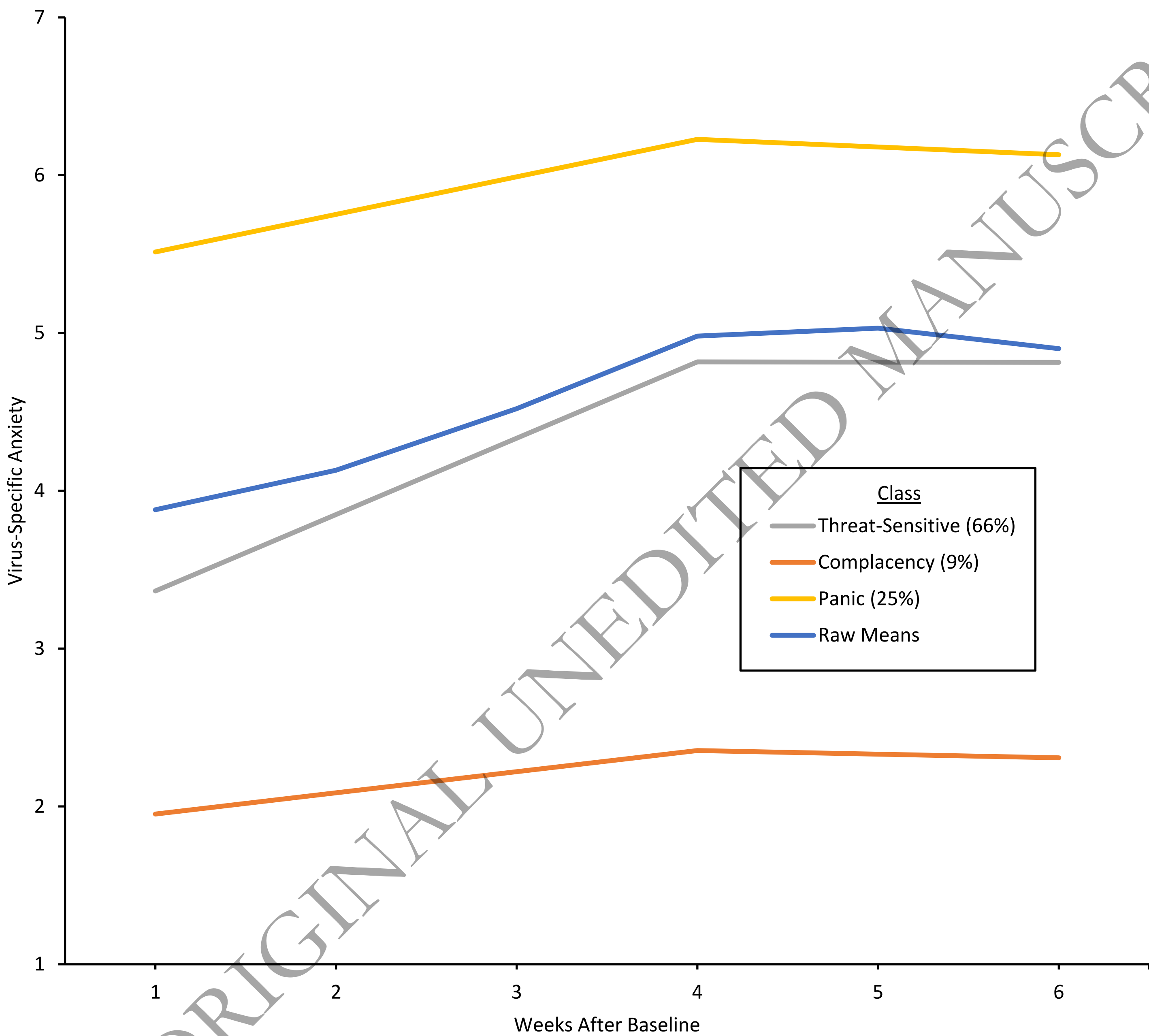

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