*Original Research Article*

# Changes in Social, Economic, and Health Risk Factors Across the Lifespan during the COVID-19 Pandemic: A Latent Transition Analysis

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**Abstract**

The COVID-19 pandemic led to unique, pervasive, and changing global impacts. It is imperative to characterize groups of individuals based on modifiable factors, and to describe how groups have been impacted by the continuing pandemic in the United States to promote health and well-being and to inform preventive interventions. We used latent transition analysis to identify subgroups of modifiable psychosocial, economic, and health risk factors; to explore subgroup shifts across time; and to assess the prevalence of non-modifiable factors associated with subgroup membership. We recruited 450 participants 18 years and older living in the United States to complete a longitudinal survey exploring health during the pandemic.

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Participants completed three waves of data collection from April to November 2020. We used latent transition analysis to identify statuses, shifts in prevalence over three waves, and the relationships of non-modifiable covariates with each status. Five statuses were identified: high risk together, low risk together, high risk alone, low risk alone, and financial risk together. Statuses were relatively stable over time; the majority (60%–66%) of participants were in statuses categorized by multiple indicators of high modifiable risk, and the largest transitions were to lower risk subgroups. Increasing age, being male, and living in an urban area were the only non-modifiable covariates associated with status membership. It is imperative to continue to scale up targeted interventions aimed at promoting resilience, well-being, financial well-being, delays in healthcare use, food insecurity, and depression among individuals in higher-risk subgroups to promote health and well-being.

**Keywords**
COVID-19 pandemic, risk and protective factors, health, economic, social

## Overview

The implementation of quarantine and stay-at-home mandates to slow the spread of coronavirus disease 2019 (COVID-19) led to non-essential business closures, loss of employment, and food shortages. This period of transition for many Americans reflected social, economic, and health-related changes with the potential for substantial impacts on long-term health and well-being (Holmes et al., 2020). Specifically, physical distancing recommendations have changed social relationships (Bierman et al., 2021) and increased unemployment (U.S. Bureau of Labor Statistics, 2021), while concerns about COVID-19 and disruptions to non-emergent care have reduced access to medical care (Czeisler et al., 2020), all of which are considered determinants of health and well-being. The negative effects of disruptive events on well-being, mental, and physical health have been reflected in prior research on disease outbreaks, quarantine, and natural disasters (Brooks et al., 2020).

In response to the call for researchers to work together to understand the consequences of the pandemic on health and well-being, identify vulnerable populations, and to inform preventive interventions (Holmes et al., 2020), we took a multidisciplinary approach. Our approach was informed by the social determinants of health and prevention science framework to examine changes in risk across three areas (psychosocial, economic, and health) during the pandemic using a person-centered approach (latent transition analysis [LTA];

Catalano et al., 2012). Person-centered approaches can be used to identify mutually exclusive and exhaustive subgroups of individuals based on a set of variables of interest (Lanza & Cooper, 2016). Such approaches acknowledge heterogeneity and describe differences between groups of individuals rather than between variables. The identification of subgroups based on combinations of risk factors can help describe characteristics of subgroups at highest risk of experiencing negative outcomes. The identification of subgroups based on clusters of co-occurring risk factors can both help to describe high-risk populations and guide the development of programs to target multiple risk factors (Leventhal et al., 2014). Specifically, we included modifiable psychosocial, economic, and health risk factors associated with potentially co-occurring long-term health outcomes, which likely changed during the pandemic (e.g., job loss) and/or could be modified by prevention programs, policies, or approaches. Identifying patterns of modifiable factors may serve as key targets for prevention efforts and can inform the development of programs that target multiple modifiable, co-occurring risk factors. For example, we included unemployment, depression, and food insecurity, all of which co-occur and benefit from secondary or targeted intervention (De Marchis et al., 2019; Oronce et al., 2021; Paul & Moser, 2009). Alternatively, we define non-modifiable factors (e.g., sex) as stable factors that are less likely to be altered through prevention programming, yet are associated with health outcomes.

Social determinants of health serve as non-medical social needs that are critical factors in improving health outcomes and reducing health disparities (Artiga & Hinton, 2018). Differences in social determinants of health can lead to health disparities and shape health outcomes both during and after the COVID-19 pandemic; thus, social determinants of health may serve as important factors to target in the prevention of negative health outcomes (Solar & Irwin, 2010). Combining the social determinants of health framework with a prevention science framework may be useful, as the prevention science framework emphasizes the identification and reduction of risk factors that precede negative health outcomes, while also promoting protective factors that decrease, mediate, or moderate negative health outcomes (Catalano et al., 2012). The identification of patterns of risk or protective factors is necessary to promote healthy development given these factors can occur at multiple levels (e.g., individual, intermediate, or structural factors), may predict multiple health outcomes, and can co-occur (Catalano et al., 2012). Therefore, we aim to characterize subgroups of individuals based on psychosocial, economic, and health risk factors; examine transitions in subgroup membership; and identify non-modifiable factors associated with subgroup membership. First, we briefly review the literature on nine psychosocial, economic, and health risk factors; their co-occurrence and relationship with health-related outcomes; and their changes during the COVID-19 pandemic. We included living alone, resilience, and subjective well-being as psychosocial risk factors; unemployment, food insecurity, and financial wellness as economic risk factors; and self-rated health, depression, and unplanned healthcare use/delay as health risk factors. We include the following psychosocial, economic, and health risk factors as they are distinct yet related factors and may be particularly relevant due to changes from the COVID-19 pandemic. Next, we provide a brief overview of each risk factor within each category and a review of the literature describing changes since the onset of the COVID-19 pandemic.

### *Psychosocial Risk Factors*

Living alone is increasing globally among people of all ages and may be a risk factor for poor mental health, loneliness, and financial difficulties (Tamminen et al., 2019). Significant changes in social interactions outside the home due to physical distancing during the pandemic may have contributed to increased risk for social isolation and other negative outcomes. During the early phase of the pandemic, living alone was associated with greater feelings of loneliness or the discrepancy between the desired and perceived quality of social relationships, especially among older adults (Luchetti et al., 2020). Although physical distancing mandates have changed over time, living alone remains a risk factor for loneliness. While living alone may be less modifiable by preventive interventions, we include living alone as a modifiable risk factor due to the strong relationships between living alone, loneliness, and social isolation during the pandemic (Luchetti et al., 2020) and the potential for disproportionate impacts of the pandemic on social relationships for individuals who live alone.

Resilience is characterized by the ability to flourish in spite of serious threats and negative life events (Masten, 2001). High levels of resilience are associated with greater social and physical functioning (Silverman et al., 2015). Conversely, low levels of resilience are related to poor coping, poor subjective well-being, and depressive symptoms (Satici, 2016; Silverman et al., 2015). A significant decline in resilience was observed during the early phase of the pandemic (Killgore et al., 2020), which may compromise individuals' ability to cope in times of adversity.

In general, individuals who report higher subjective well-being maintain better physical health and live longer than those with lower subjective well-being (Diener et al., 2017). Similar to resilience, multiple studies have indicated well-being significantly decreased since the onset of the pandemic (Vindegaard & Benros, 2020). Thus, higher subjective well-being may be a protective factor against the challenges the pandemic presents.

## *Economic Risk Factors*

Unemployment is closely related to distress, depression, and anxiety and has been associated with loss of housing, more hospital visits, and increases in suicide (Margerison-Zilko et al., 2016; Paul & Moser, 2009). Increased unemployment since the COVID-19 pandemic (U.S. Bureau of Labor Statistics, 2021) has impacted some communities more so than others (Montenovo et al., 2020) and led to the implementation of increased federal financial interventions (e.g., stimulus checks and supplemental unemployment insurance).

Food insecurity, or uncertain access to adequate food, is associated with significant negative physical and mental health outcomes across the lifespan, including increased risk for chronic disease and depression and decreased diet quality, sleep quality, and oral health (Coleman-Jensen et al., 2019; Gundersen & Seligman, 2015). During the early phases of the pandemic, food insecurity increased at alarming rates, disproportionately impacting vulnerable populations who were already at high risk for food insecurity and exacerbating existing disparities (Wolfson & Leung, 2020a, 2020b). As the pandemic continued, however, decreases in food insecurity were evident among individuals who received supplemental unemployment insurance (Raifman et al., 2021). While decreases were significant, individuals receiving supplemental unemployment insurance experienced higher rates of food insecurity compared to those who remained employed (Raifman et al., 2021).

Financial wellness is the subjective perception of financial status (Joo, 2008). Low financial wellness is associated with negative mental health outcomes (Kiely et al., 2015) and low overall well-being (Weinstein & Stone, 2018). A study from early in the pandemic found most U.S. adults were worried about the impact of the pandemic on their employment and finances (Wilson et al., 2020). Specifically, factors such as job insecurity were associated with greater anxiety and depressive symptoms (Wilson et al., 2020). Thus, concerns about perceived financial wellness throughout the pandemic may be a salient risk factor.

## *Health Risk Factors*

Self-rated health is a useful and comprehensive screening tool for general health status (Jylhä, 2009). Low self-rated health is associated with decreased ability to perform activities of daily living (Tomioka et al., 2017), increased prevalence of chronic health conditions (Bamia et al., 2017), and increased risk of healthcare use (Chamberlain et al., 2014). Conversely, high self-rated health is positively associated with maintaining a healthy diet and physical activity (Manderbacka et al., 1999), life satisfaction, and lower depression

(Cai et al., 2017). Self-rated health was observed to decrease after the onset of the pandemic (Gao et al., 2020). In the United States, adults with poor self-rated health also reported decreased emotional support during the pandemic (Philpot et al., 2021). Taken together, these findings suggest the experience of the pandemic may have negative impacts on self-rated health.

Poorer self-rated health, living alone, and unemployment may be associated with depressive symptoms (Ambresin et al., 2014; Paul & Moser, 2009), which in turn can negatively impact financial wellness and social relationships and lead to an increased risk for chronic disease (Dunbar et al., 2008; Naicker et al., 2013). A systematic review of current evidence of the mental health consequences of the COVID-19 pandemic found significant increases in depressive symptoms among healthcare workers and community samples, with worsening symptoms among individuals with preexisting psychiatric disorders (Vindegaard & Benros, 2020). With the increasing prevalence of depression, it is critical to consider how depression symptoms may cluster with other risk factors during the pandemic.

Access to medical care changed substantially since the onset of the COVID-19 pandemic in March 2020, with 41% of adults in the United States delaying or avoiding medical care in June 2020 (Czeisler et al., 2020). Preventive healthcare use also substantially declined. Routine vaccinations and colonoscopies were 18% and 90% lower, respectively, in March/April of 2020 than in the prior two years (Whaley et al., 2020). Individuals experiencing unplanned medical care, hospitalization, or delayed primary care may be at risk of subsequent adverse health outcomes and related risk factors.

## Current Study

Given that risk factors such as living alone, financial wellness, and depression can co-occur, the first aim of this study was to examine subgroups of individuals based on combinations of modifiable psychosocial, economic, and health risk factors from April to November of 2020. Due to the changing landscape of the COVID-19 pandemic, the second aim was to examine shifts or transitions in the prevalence of subgroup membership during the pandemic using LTA. Our third aim was to identify non-modifiable predictors associated with each subgroup, which can further describe subgroups at the highest risk, particularly as the pandemic has exacerbated inequalities among vulnerable populations (Berkowitz et al., 2021). Together, identifying subgroups based on patterns of modifiable risk factors, changes in prevalence in subgroup membership during the pandemic, and non-modifiable factors related to higher-risk subgroups can identify populations most in need of targeted interventions. Due to the exploratory nature of this study, we do not specify a priori hypotheses.

# Methods

## *Participants and Procedures*

We used Prolific Academic (See https://researcher-help.prolific.co/hc/en-gb/articles/360013275033-How-do-I-cite-Prolific-) to recruit adults 18 years and older living in the United States to complete a longitudinal online study exploring changes in health, well-being, and health behaviors during the COVID-19 pandemic (Weaver et al., 2021). We recruited a representative sample of 400 participants based on age, sex, and race to participate in three waves of data collection in 2020. We noticed that less than 10% of participants recruited had a child aged 18 months to 12 years old. As there are 63.1 million parents in the United States, and parents may have experienced substantial disruptions during the COVID-19 pandemic due to changes in child care, we recruited an oversample of 50 parents with a child aged 18 months to 12 years old (U.S. Census Bureau, 2020). Wave 1 was available between April 21 to May 6, Wave 2 between July 15 to 31, and Wave 3 between November 1 to 20. Participants were paid between $8 to $10.50 for participation in each wave of data collection. Participants were excluded from analysis if they did not accurately complete at least half of the attention checks or complete the survey in less than three standard deviations of the mean completion time. Of the invited participants, 396 (80%) met inclusion criteria at Wave 1 of data collection. We invited the 396 participants to complete Waves 2 and 3. Wave 2 was completed by 305 (77%) participants, and 258 (65%) participants completed Wave 3. This study was certified as exempt by the Washington State University's Institutional Review Board. All participants provided written consent prior to beginning the survey.

## *Measures*

*Demographic Characteristics.* We collected self-reported demographic data including age, sex, height, weight, race, marital status, education level, geographic location, household income, and history of chronic disease.

*Non-Modifiable factors (Covariates).* We include age, sex, race, CDC risk for severity of COVID-19, education level (greater or less than a 4-year degree), and geographic location (urban and non-urban) as non-modifiable covariates. Due to the small sample size of Asian, Hispanic/Latinx, and other races, we created two groups: White and underrepresented groups. Using Wave 1 data and recognizing risk could change over time, we created a dichotomous variable indicating risk for severity of COVID-19 from self-reported data captured, including age, height, weight, and history of chronic disease (Centers for Disease Control and Prevention, 2020). We asked participants if they had been diagnosed with any of the 15 chronic diseases provided; participants were able to select all that apply. If the participant indicated they were age 65 or older or had at least one of the following risk factors: lung disease, asthma, heart conditions, immunocompromised, diabetes, chronic kidney disease, liver disease, or a body mass index greater than 40 (calculated from self-reported height and weight), they were coded as being at higher risk for severe COVID-19 (1). If participants did not indicate any of the risk factors for severe COVID-19 described above, they were coded as low risk (0). We did not include marital status or household income as non-modifiable covariates in this analysis to avoid overlap with predictors of latent statuses (i.e., living alone, food insecurity, and unemployment).

*Modifiable Factors (Predictors of Latent Statuses).* We collected variables at all three waves and coded for higher risk (1) or lower risk (0). For *psychosocial Risk Factors*. We included living alone, resilience, and subjective well-being as psychosocial risk factors. Participants were asked how many individuals were currently living in their household, and responses were recoded to indicate living alone (1) or living with others (0). Resilience was measured using the validated 6-item Brief Resilience Scale (BRS; Smith et al., 2008) with response options ranging from 1 (strongly disagree) to 5 (strongly agree) with higher scores indicated higher resilience. Example items include, “I tend to bounce back quickly after hard times” and “I usually come through difficult times with little trouble.” Psychometric testing of the BRS has demonstrated internal consistency, convergent and discriminant validity, and test–retest reliability in undergraduate, clinical, and community samples (Smith et al., 2008). Average scores were grouped using established cut-points 1.00 to 2.99 = low, 3.00 to 4.30 = normal, and 4.31 to 5.00 = high resilience (Smith et al., 2008). In the current study, we separated low resilience (1) from normal or high resilience (0). Subjective well-being was measured with the question: “Taking all things together, how satisfied are you with your life as a whole these days?” Participants responded on a 4-point scale, and responses were coded as negative (not at all satisfied or not very satisfied; 1) and positive (satisfied or very satisfied; 0).

*Economic Risk Factors*. We included unemployment, food insecurity, and financial wellness as economic risk factors. Participants were asked their current employment status with response options of unemployed, including furloughed; part-time; full-time; not seeking work; or prefer not to answer. Items were coded as unemployed (1) or other responses (0).

Food insecurity was assessed using the validated 2-item food insecurity screening tool (Hager et al., 2010). The two items were “We have been worried whether our food would run out before we got money to buy more” and “The food we bought didn’t last and we didn’t have money to get more.” If participants answered “sometimes” or “often true” to at least one of the items, they were scored as food insecure (1). Participants who indicated "never true" to both items were scored as food secure (0). Participants completed the 8-item Personal Financial Well-being (PFW) scale (Prawitz et al., 2006), and responses were coded based on national scale norms. Items include, "How satisfied are you with your present financial situation?" and "How stressed do you feel about your personal finances in general?" Psychometric testing of the PFW has demonstrated internal consistency, convergent and discriminant validity, and reliability in a community sample (Prawitz et al., 2006). Participants were coded as at or below the national average (1) or above the national average (0). For *health Risk Factors*. We included self-rated health, depression, and unplanned/delayed healthcare use as health risk factors. Participants were asked, "In general, would you say your health is …" with a 5-point response scale ranging from poor (1) to excellent (5). Negative responses (poor and fair; 1) were separated from positive responses (good, very good, and excellent; 0). Depression symptoms were measured using the 10-item Center for the Epidemiological Studies of Depression Short Form (CES-D-10; Radloff, 1977) in which participants indicated frequency of each indicator (rarely/none of the time = 0 to all the time = 3). Example items include, "I felt depressed" and "I felt everything I did was an effort." Psychometric testing of the CES-D-10 in clinical and community populations has demonstrated internal consistency, convergent and divergent validity, and sensitivity (Björgvinsson et al., 2013; Radloff, 1977). A sum score was calculated and based on established interpretation of the CES-D-10, scores $\geq$ 10, which indicate symptoms of depression (1), were separated from scores $<$ 10 (0). Participants were asked a series of healthcare use questions including if they had accessed care in the emergency department, had an unplanned hospitalization, were unable to access preventive care, delayed or canceled a primary care appointment or dental procedure, or delayed filling a prescription. For the current study, we aggregated and dichotomized responses into participants who indicated experiencing at least one item (1) and those who did not experience any of the items (0).

## *Data Analysis*

Data were screened for missing values. Missing data on covariates were minimal (only five participants did not indicate sex) and handled using listwise deletion; full information maximum likelihood was used for missing data on predictors of statuses. We used latent transition analysis (LTA) to identify subgroups, referred to as statuses in LTA, of individuals based on their responses to psychosocial, health, and economic risk factors. We first conducted a series of latent class analyses (LCA). We examined model fit statistics including Bayesian information criterion (BIC), Akaike information criterion (AIC), and sample-size adjusted BIC (SABIC), with lower values indicating better relative fit. We also examined entropy with higher values indicating better fit. Previous research indicates the BIC performs best to assess the number of classes (Nylund et al., 2007; Tein et al., 2013). Model selection was based on interpretability, parsimony, entropy, and BIC. After running each model at the three waves separately, we conducted a series of LTAs to describe how individuals shifted between statuses over time. LTA identifies estimates of status (i.e., latent class) membership, as well as the probability of transitioning from one status to another. Item responses were used to describe the statuses and were constrained across time to determine transitions between statuses across three waves of data collection. We then used separate logistic regression analyses to examine relationships between statuses and covariates: age, sex, CDC risk for severe COVID-19, education level, geographic location, and race to test whether non-modifiable factors predicted status membership at Wave 1. Analyses were conducted in Mplus 8.

## Results

Socio-demographic characteristics of the study sample are presented in Table 1. We estimated LCA models with 1 through 5 classes for each wave of data collection (Appendix A) and found 3 or 4 classes were the best solution for each wave. Guided by preliminary LCA results, LTAs with 2 to 5 statuses were compared (Table 2). The BIC continued to decline through the 5-status model. Entropy was similar for the 3-, 4-, and 5-status models. Compared to the 4-status solution, the additional status in the 5-status solution was characterized by a status of low-risk individuals who lived alone. As there were two high-risk statuses that were differentiated by living alone, and given that the context of the COVID-19 pandemic has altered social interactions outside of the home, we selected the 5-status solution.

Item-response probabilities, latent status prevalence, and transition probabilities for the 5-status model are presented in Table 3. All item-response probabilities were held to be equal across the three waves to allow for interpretation of transitions in statuses over time. The first status, labeled *high risk together* (34–38% prevalence), was characterized by living with others, low resilience and well-being, high risk for depression, healthcare use or delay, and low financial well-being. Risk for depression was frequently endorsed by individuals in the high risk together status (.88), while low resilience (.58), low well-being (.68), low financial well-being (.67), and delayed healthcare use (.50) were less frequently endorsed. The second status, *low risk together* (26–31% prevalence), was characterized by living with others and low levels of most/all risk factors. The third status, *high risk alone* (10–12% prevalence), was characterized by living alone, low resilience and well-being, high risk for depression, low financial well-being, and food

**Table 1.** Socio-demographic Characteristics of the Sample.

| | Mean (*SD*) or *n* (%) |
|---|---|
| Age | 44.95 (15.88) |
| Sex | |
| Men | 185 (46.7%) |
| Women | 206 (52.0%) |
| Race | |
| White | 270 (68.2%) |
| Hispanic or Latino | 22 (5.6%) |
| Asian | 29 (7.3%) |
| Black | 47 (11.9%) |
| Other | 27 (6.8%) |
| Marital status | |
| Single | 127 (32.1%) |
| Married/committed relationship | 210 (53.0%) |
| Divorced/separated | 54 (13.6%) |
| Other | 5 (1.3%) |
| Education level | |
| ≤ 4-year degree | 202 (51.0%) |
| ≥ 4-year degree | 194 (49.0%) |
| Geographic location | |
| Urban | 93 (23.5%) |
| Suburban | 189 (47.7%) |
| Mid-size city or town | 39 (9.8%) |
| Rural | 75 (18.9%) |
| Household income | |
| < $35,000/year | 118 (29.8%) |
| $35,000–51,999 | 88 (22.2%) |
| $52,000 to 73,999 | 72 (18.2%) |
| $74,000 to 99,999 | 55 (13.9%) |
| Over $100,000 | 56 (14.1%) |
| CDC risk | |
| Low risk | 246 (62.1%) |
| High risk | 150 (37.9%) |

*Note.* $N = 396$.

insecurity. Within the high risk alone status, living alone (1.00), low well-being (.82), low financial well-being (.89), and depression risk (.87) were frequently endorsed, whereas food insecurity (.51) and low resilience (.59), while prevalent and indicative of the status, were slightly less frequently endorsed. The fourth status, *low risk alone* (8–9% prevalence), was characterized by living alone and low levels of most/all risk factors. The fifth

**Table 2.** Model Fit for Latent Statuses Across Wave 1 to Wave 3 Data Collection.

| No. of Statuses | Log-Likelihood | BIC | SABIC | AIC | Entropy |
|---|---|---|---|---|---|
| 2 | −4,683.248 | 9,504.07 | 9,431.09 | 9,412.50 | .924 |
| 3 | −4,542.420 | 9,330.08 | 9,199.98 | 9,166.84 | .935 |
| 4 | −4,414.670 | 9,206.17 | 9,006.27 | 8,955.34 | .934 |
| 5 | −4,302.184 | 9,136.71 | 8,854.32 | 8,782.37 | .938 |

*Note.* BIC = Bayesian information criterion, AIC = Akaike information criterion, SABIC = sample-size adjusted Bayesian information criterion.

status, *financial risk together* (14–18% prevalence), was characterized by living with others, low financial well-being (1.00), and food insecurity (.60).

From Wave 1 to Wave 2, transitions were minimal except for 9% of individuals in high risk alone transitioning to low risk alone and 16% transitioning from financial risk together to low risk together. Overall, status membership was stable from Wave 2 to Wave 3, with 8% of individuals in financial risk together transitioning to low risk together.

Based on the transitions from financial risk together to the low risk together status, we included a post-hoc logistic regression analysis investigating whether receipt of the initial COVID-19 stimulus check (reported at Wave 2 in July 2020) predicted this transition. Of the 305 participants who completed Wave 2, 83% of participants ($n = 253$) received the initial stimulus check from the government. Receipt of the initial stimulus check did not have a significant influence on the odds of staying in the financial risk together status compared to transitioning to the low risk together status.

The prevalence of non-modifiable risk factors by latent status membership at Wave 1 and odds ratios with the low risk together status as a reference group are presented in Table 4. The only non-modifiable predictors associated with status membership were age, sex, and geographic location. Compared to the low risk together status, increased age was associated with a lower likelihood of being in the high risk together status; men had a lower likelihood of being in the high risk together, low risk alone, and financial risk together statutes, and living in an urban area was associated with a higher likelihood of being in the low-risk alone status.

## Discussion

The changing landscape of the COVID-19 pandemic has profoundly impacted multiple determinants of health. We employed a person-centered approach to identify subgroups based on modifiable psychosocial, economic, and health risk factors and to assess transitions in membership. This approach identified vulnerable subgroups during the pandemic that were relatively stable over

**Table 3.** Item-Response Probabilities, Proportions, and Transition Probabilities for the Selected LTA Model.

| | Status 1 High Risk Together | Status 2 Low Risk Together | Status 3 High Risk Alone | Status 4 Low Risk Alone | Status 5 Financial Risk Together |
|---|---|---|---|---|---|
| Item response probabilities | | | | | |
| Living alone | .00 | .00 | **1.00** | **1.00** | .00 |
| Low resilience | **.58** | .04 | **.59** | .00 | .09 |
| Low well-being | **.68** | .07 | **.82** | .13 | .18 |
| Unemployed | .29 | .19 | .29 | .17 | .26 |
| Food insecure | .38 | .10 | **.51** | .14 | **.60** |
| Low financial well-being | **.67** | .07 | **.89** | .27 | **1.00** |
| Low self-rated health | .26 | .10 | .36 | .01 | .17 |
| Depression risk | **.88** | .17 | **.87** | .24 | .32 |
| Delayed healthcare use | **.50** | .42 | .49 | .32 | .40 |
| The proportion of statuses at | | | | | |
| Wave 1 (April 2020) | 38% | 26% | 11% | 8% | 18% |
| Wave 2 (July 2020) | 36% | 31% | 10% | 8% | 15% |
| Wave 3 (November 2020) | 34% | 31% | 12% | 9% | 14% |
| Transition probabilities from Wave 1 to Wave 2 | | | | | |
| High risk together | .93 | .05 | .02 | .00 | .00 |
| Low risk together | .00 | .99 | .00 | .01 | .00 |
| High risk alone | .03 | .00 | **.88** | **.09** | .00 |
| Low risk alone | .00 | .00 | .05 | .95 | .00 |
| Financial risk together | .00 | **.16** | .00 | .00 | **.84** |
| Transition probabilities from Wave 2 to Wave 3 | | | | | |
| High risk together | .95 | .00 | .05 | .00 | .00 |
| Low risk together | .00 | .98 | .00 | .02 | .00 |
| High risk alone | .00 | .00 | 1.00 | .00 | .00 |

*(continued)*

**Table 3.** (continued)

| | Status 1 High Risk Together | Status 2 Low Risk Together | Status 3 High Risk Alone | Status 4 Low Risk Alone | Status 5 Financial Risk Together |
|---|---|---|---|---|---|
| Low risk alone | .00 | .00 | .00 | .96 | .04 |
| Financial risk together | .00 | **.08** | .00 | .00 | .92 |

*Note.* Bold font indicates item-response probabilities greater than .50. Transition probabilities are the probability of membership in a status at *wave + 1* conditional on membership in status at *wave*. Transition probabilities sum to 1.0 across each row (with rounding errors).

time. Statuses were differentiated by high and low risk across multiple determinants of health and either living alone or with others, with one exception: the financial risk together status. The financial risk together status was characterized by high financial risk and low psychosocial and health risk. The three largest transitions across all three waves of data collection were from a higher risk status to a lower risk status (i.e., from financial risk together to low risk together).

Interestingly, low self-rated health and unemployment were not endorsed and did not co-occur with other factors. The low rates of endorsement are surprising considering unemployment has significantly increased since the pandemic, and previous research suggests a close connection between unemployment, depression, and self-rated health (Ambresin et al., 2014; Paul & Moser, 2009). In our study, these factors were less salient to statuses indicative of higher risk. However, the high risk alone status was characterized by food insecurity and low financial well-being, whereas the high risk together status was characterized by low financial well-being but not food insecurity. While we did not assess whether individuals were living with children or other adult family members, our findings are somewhat contradictory to the substantial literature indicating families experience higher rates of food insecurity (Coleman-Jensen et al., 2019; Gundersen & Seligman, 2015). Rather, one potential explanation for this finding is that living alone could hinder the ability to combine household resources, which may be a relevant risk factor during the pandemic.

The transitions from the financial risk together to the low risk together statuses suggest that financial programs and policies that were implemented between April 2020 and July 2020 may have been effective in lowering financial distress and food insecurity among an at-risk group. While our post-hoc analysis indicated that receipt of the initial government stimulus check was not associated with transitioning from the financial risk together status to

**Table 4.** Proportions and Odds Ratios of Non-Modifiable Risk Factors by Latent Status Membership at Wave 1.

| | *n* | Status 1 High Risk Together | | Status 2 Low Risk Together | Status 3 High Risk Alone | | Status 4 Low Risk Alone | | Status 5 Financial Risk Together | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | OR [95% CI] | | | OR [95% CI] | | OR [95% CI] | | OR [95% CI] |
| Age | 395 | — | **0.96 [0.94–0.98]** | — | — | 1.02 [0.99–1.04] | — | 1.02 [0.99–1.06] | — | 0.99 [0.97–1.01] |
| Sex | | | | | | | | | | |
| Female | 206 | 41% | — | 20% | 12% | — | 8% | — | 20% | — |
| Male | 184 | 32% | **0.43 [0.24–0.78]** | 36% | 10% | **0.45 [0.21–0.96]** | 8% | 0.56 [0.23–1.38] | 15% | **0.41 [0.19–0.88]** |
| CDC risk | | | | | | | | | | |
| Low risk | 246 | 42% | — | 25% | 10% | — | 6% | — | 17% | — |
| High risk | 150 | 32% | 0.64 [0.35–1.04] | 28% | 12% | 1.09 [0.49–2.42] | 10% | 1.36 [0.56–3.31] | 18% | 0.91 [0.41–2.03] |
| Education level | | | | | | | | | | |
| < 4-year degree | 202 | 39% | — | 21% | 8% | — | 9% | — | 23% | — |
| > 4-year degree | 194 | 36% | 0.60 [0.35–1.04] | 32% | 13% | 1.21 [0.55–2.65] | 7% | 0.49 [0.20–1.18] | 12% | 0.36 [0.20–1.18] |
| Geographic location | | | | | | | | | | |
| Non-urban | 303 | 39% | — | 27% | 10% | — | 18% | — | 5% | — |
| Urban | 93 | 34% | 0.96 [0.49–1.89] | 24% | 11% | 1.195 [0.49–2.89] | 16% | **3.41 [1.41–8.25]** | 16% | 0.96 [0.41–2.28] |
| Race | | | | | | | | | | |
| Non-White | 125 | 38% | — | 18% | 10% | — | 7% | — | 26% | — |
| White | 270 | 36% | 0.72 [0.39–1.32] | 27% | 11% | 0.84 [0.36–1.95] | 8% | 0.82 [0.31–2.16] | 18% | 0.64 [0.28–1.44] |

*Note*. Odds ratios use the *low risk together* status as a reference group. We do not include proportions by age as we included age as a continuous variable. CDC Risk = for severe COVID-19. Significant odds ratios are in bold font.

the low risk together status, the lack of a significant association may be attributed to insufficient variability across statuses, as the majority of participants (83%) received the first stimulus check. While we did not identify a direct influence in decreasing risk with the implementation of a single stimulus check, our results suggest COVID-19 relief and recovery policies and programs have led to improvements, similar to the reductions of food insecurity associated with supplemental unemployment insurance (Raifman et al., 2021). Additional research on the impacts of federal financial supplementation is warranted.

Lastly, our results indicated age, sex, and geographic location were the only non-modifiable factors associated with status membership. Compared to the low risk together status: older adults were less likely to be in the high risk together status; men were less likely to be in the high risk together, low risk alone, and financial risk together statuses; and individuals living in an urban area were more likely to be in the low risk alone status, compared to the low risk together status. The lack of differentiation in subgroup membership across non-modifiable factors, while surprising, highlights the pervasive impacts of the pandemic in the United States. However, due to our sample size, we were unable to investigate differences across sexes and multiple ethnic groups, which are known to be differentially impacted by the pandemic.

The longitudinal study design allows us to disentangle how risks changed since the onset of the pandemic. Understanding the synergy of the combination of risk factors may be important to promote overall health and well-being and to inform preventive interventions, particularly with the differing impacts of the pandemic throughout the United States (Holmes et al., 2020). Our results indicate financial interventions may be effective for individuals who are solely characterized by high financial risk. Thus, secondary preventive programs or policies that target financial risk may benefit from screening and targeting individuals who are high in financial risk without other (i.e., psychosocial or health) risk factors. Alternatively, screening and comprehensive secondary preventive interventions are warranted to address these co-occurring risk factors among individuals who indicate low resilience, low well-being, low financial well-being, risk for depression, and delayed healthcare use. Future research will benefit from understanding the differential effects of the pandemic, as evident from unique subgroups of risk and the potential implications on long-term health outcomes.

Our results suggest subgroups of risk have been relatively stable, with the largest transitions moving to a lower risk subgroup, which is surprising given the rapid changes associated with the pandemic, particularly from July 2020 to November 2020. In comparison to prior research using LTA (Bray et al., 2016; Hultgren et al., 2019; Lanza & Collins, 2008; Vaziri et al., 2020), the transition probabilities in the current study are very small, suggesting substantial stability over time. Status stability over time could be attributed to the timing of data collection or due to attrition across the three waves of data collection. Our first wave of data collection occurred in late April 2020, almost a month after COVID-19 was declared a global pandemic. As such, relevant transitions may have occurred prior to our first wave of data collection, which could offer a possible explanation for the stability over time. Alternatively, we postulate that in alignment with the selection, optimization, and compensation model (Baltes et al., 1998), individuals may be effectively managing change through the selection of priorities, optimization of resources, and compensatory response to the changing environment. Future research would benefit from not only identifying subgroups based on risk factors, but also including the access or availability and use of resources to better inform both universal and secondary preventive interventions.

Our study is mainly descriptive of change and the impact of the COVID-19 pandemic on modifiable risk factors across the lifespan. While we were unable to capture pre-pandemic data, the stability of subgroups during the pandemic indicates little to no improvement in the prevalence among high-risk subgroups. As the high risk together subgroup was the largest profile (34–38%) and the majority of our sample (60%–66%) was in a subgroup characterized by higher risk, scaling up interventions to reduce multiple modifiable risks is necessary. Taken together, screening for modifiable risk factors including resilience, well-being, depression, delays in healthcare use, financial well-being, and food insecurity (i.e., social determinants of health), and the scaling up of secondary preventive interventions are viable pathways for promoting health and well-being during and after the pandemic.

## Appendix A

*Model Fit for Latent Classes for each Wave (Wave 1 to Wave 3).*

| No. of Statuses | Log-Likelihood | BIC | SABIC | AIC | Entropy |
|---|---|---|---|---|---|
| Wave 1 | | | | | |
| 1 | −2,144.70 | 4,343.24 | 4,314.68 | 4,307.41 | — |
| 2 | −2,029.11 | 4,171.87 | 4,111.59 | 4,096.23 | 0.68 |
| 3 | −2,008.82 | 4,191.09 | 4,099.08 | 4,075.63 | 0.79 |
| 4 | −1.991.00 | 4,215.28 | 4,091.53 | 4,060.01 | 0.73 |
| 5 | −1,980.11 | 4,253.30 | 4,097.83 | 4,058.21 | 0.78 |
| Wave 2 | | | | | |
| 1 | −1,614.61 | 3,280.69 | 3,252.15 | 3,247.21 | — |
| 2 | −1,510.43 | 3,129.54 | 3,069.29 | 3,058.86 | 0.70 |
| 3 | −1,490.08 | 3,146.04 | 3,054.07 | 3,038.15 | 0.79 |
| 4 | −1,477.23 | 3,177.54 | 3,053.85 | 3,032.45 | 0.80 |

*(continued)*

(continued)

| No. of Statuses | Log-Likelihood | BIC | SABIC | AIC | Entropy |
|---|---|---|---|---|---|
| 5 | −1,467.22 | 3,214.74 | 3,059.34 | 3,032.45 | 0.85 |
| Wave 3 | | | | | |
| 1 | −1,360.25 | 2,770.47 | 2,741.94 | 2,738.50 | — |
| 2 | −1,255.73 | 2,616.96 | 2,556.72 | 2,549.45 | 0.75 |
| 3 | −1,236.56 | 2,634.16 | 2,542.22 | 2,531.12 | 0.75 |
| 4 | −1,222.51 | 2,661.58 | 2,537.93 | 2,523.01 | 0.82 |
| 5 | −1,213.59 | 2,699.27 | 2,543.93 | 2,525.18 | 0.80 |

*Note*. BIC = Bayesian information criterion, AIC = Akaike information criterion, SABIC = Sample-size adjusted Bayesian information criterion.

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This article does not contain any studies with animals performed by any of the authors.

## Ethical Approval

All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

## Informed Consent

Informed consent was obtained from all individual participants included in the study.

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