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Psychosocial factors associated with preventive pediatric care during the COVID-19 pandemic

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A R T I C L E I N F O

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A B S T R A C T

Background: Identifying the factors that predict non-adherence to recommended preventive pediatric care is necessary for the development of successful interventions to improve compliance.
Purpose: Given the substantial decline in well-child visits and influenza vaccinations, we sought to examine sociodemographic (i.e., parent age, education, employment status, child age, insurance coverage, household size, race and ethnicity, income, COVID-19 incidence in state) and psychosocial (i.e., child temperament, parent mental health, parent personality traits) factors associated with preventative pediatric care (well-child visits, influenza vaccines) during the COVID-19 pandemic.
Methods: As part of a larger, ongoing study, 1875 parents (96% mothers, 65% age 35 or younger, 58% with a college degree) reported whether they had missed any recommended or scheduled well-child visits since the pandemic and whether they had vaccinated their child against the flu. Using data collected during fall 2020, we examine differences in these health outcomes across social/demographic factors and psychological profiles. In addition, we use lasso logistic regression models to (1) estimate the accuracy with which we can predict adherence from these characteristics and (2) identify factors most strongly, independently associated with adherence.
Results: Parent psychological factors were associated with outcomes above and beyond known demographic and social factors. For example, parent industriousness and orderliness were associated with greater likelihoods of attending well-child visits and vaccinating children, while parent conservatism and creativity were associated with lower rates. We also replicate prior work documenting that health insurance, income, and household size are major factors in receiving adequate pediatric care.
Conclusions: Adherence to preventive pediatric care varies as a function of psychological factors, suggesting that the current system of pediatric care favors some psychological profiles over others. However, the specific traits associated with non-adherence point to potentially fruitful interventions, specifically around increasing functional proximity.

1. Introduction

Pediatric preventive healthcare, including well-child visits and vaccinations, is one of the cornerstones of public health in the United States. It serves to ensure that infants and children are achieving key physical developmental milestones, provides developmental screening and proactive identification of special health care needs, and facilitates referral to necessary specialist services for physical and behavioral health in the early years. The American Association of Pediatrics publishes a periodicity schedule (Hagan et al., 2017) for the timing, frequency, and goals of specific visits beginning at birth and extending through age 21.

Not surprisingly, despite the rapid development of telehealth pediatric services in the last year (Patel et al., 2020), pediatric service utilization has dropped significantly since the beginning of the COVID-19 pandemic (Centers for Medicare and Medicaid Services, 2020). Consequently, we see declines in pediatric vaccination rates (Santoli, 2020), in part due to persistent concerns by parents regarding the safety of vaccines. In addition to reduced protection against serious chronic illness, non-adherence to the recommended well-child visit schedule is associated with a greater risk of hospitalization (Tom et al., 2010) and later detection of autism and other cognitive impairments (Daniels and Mandell, 2013).

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An empirically grounded understanding of specific variables associated with children missing preventive health care visits and vaccinations could be used to develop targeted intervention strategies aimed at improving adherence. While parents face new challenges during the pandemic, such as fear of exposure to COVID-19, some barriers to participation — including lack of insurance, having more children in the household, and being an older parent (Wolf et al., 2020) — predate COVID-19. These factors may have been exacerbated (Cheng et al., 2020) since the pandemic's onset by widespread increases in financial instability and fears of contracting the virus. Importantly, there is extensive evidence that the effects of the pandemic have affected families unequally, increasing already-existing inequities between racial groups (Valenzuela et al., 2020); this has likely contributed to observed differences in healthcare utilization (Johnson, 2020) among specific subgroups. Other family demographic variables are associated with pediatric preventive care, such as parent education and household size (for a review see Kataoka-Yahiro and Munet-Vilaro, 2002).

Most research has focused on structural and demographic factors at play in pediatric adherence, but there are other important factors to consider. Parent psychosocial characteristics – in particular parent mental health and personality – is largely understudied in pediatric care, despite well-documented associations between these characteristics and health behaviors (Bogg and Roberts, 2004; Kataoka-Yahiro and Munet-Vilaro, 2002). Notably, personality traits (e.g., industriousness and organization) are associated with adherence, both to prescribed medicine regimens (Hill and Roberts, 2011) and public health initiatives (Bogg and Milad, 2020), even after accounting for sociodemographic factors. Early investigations have identified associations between parent characteristics and adherence to pediatric primary care recommendations (Mourão et al., 2020) and child medicine (Durkin et al., 2020). For example, poor parental mental health – including stress and depression – is associated with increased use of pediatric services (Kataoka-Yahiro and Munet-Vilaro, 2002). Similarly, child temperament – often measured with parent-report instead of self-report – has indicated associations between negative affect (e.g., depression) and increased use of pediatric care (Seligman, 1996; Wertlieb et al., 1988).

If parental psychosocial characteristics account for preventive healthcare adherence above and beyond structural barriers, the public health implications in terms of designing strategies to increase adherence are highly important. More specifically, the identification of traits associated with non-adherence points a spotlight on qualities to target. For example, if parents low on trait industry are less likely to vaccinate, this may suggest that barriers to vaccination include ease of access (as it requires effort and industry to navigate the system), or attitudes and beliefs related to industriousness, or both. Broadly speaking, psychosocial characteristics associated with pediatric care could potentially be used to identify and target parents at the greatest risk for non-adherence to recommended well-child visits and vaccinations or inform the tailoring of messages to maximize compliance with these recommendations (Hirsh et al., 2012). However, it remains to be seen whether parent psychosocial characteristics hold substantive predictive power after accounting for systemic barriers, such as those described above. Moreover, given the legitimate fear of exposure to COVID-19 during any outside-home activity and heightened anxiety overall, it may be that psychological factors play an even larger role in healthcare decision-making under pandemic conditions.

In the current study, we examine sociodemographic (i.e., parent age, education, employment status, child age, insurance coverage, household size, race and ethnicity, income, COVID-19 incidence in state) and psychosocial (i.e., child temperament, parent mental health, parent personality traits) factors associated with preventative pediatric care (well-child visits, influenza vaccines) during the COVID-19 pandemic. We were especially interested in determining the extent to which parental psychosocial characteristics predict pediatric care over and above other factors during the COVID-19 pandemic. These data are a subset of participants and variables from a larger, ongoing study of families with young children.

2. Methods

2.1. Participants

Data are drawn from an ongoing study – the Rapid Assessment of Pandemic Impact on Development-Early Childhood (RAPID-EC) – a nationally representative sample of parents of children ages 5 and younger (approved by the University of Oregon IRB, # 03252020.031). Specifically, for the current paper we employed survey data that were collected bi-weekly between November 1 and December 3, 2020. These data were collected from 1875 parents (96% mothers, 65% age 35 or younger, 58% with a college degree). Each parent was from a different family. Parents were recruited through a variety of sources, including ParentsTogether, Amazon Mechanical Turk, Kinedu, and Facebook. With these data, we have 90% power to detect group differences as small as $d = 0.19$ and correlations as small as $r = 0.07$. (Power estimates of group differences are based on the smallest group size, i.e., 588 parents reported missing a well-child visit during the pandemic. Correlations are based on the total sample size.)

2.2. Measures

Preventive care outcomes. We focus on two primary outcomes. The first outcome is whether children **successfully attended a well-baby/well-child visit**, assessed using the question, "Have you missed a well-baby/well-child check-up since the coronavirus (COVID-19) pandemic began?" For consistency with the research questions, we coded responses as 1 (No, did not miss) and 0 (Yes, did miss), so positive associations with this outcome indicate compliance with the well-child schedule. We note here that this question assesses whether any well-child visit was missed for any child in the household. Our second outcome was whether children had **already received the annual influenza vaccination** for the 2020–2021 season. We chose to focus on the behavioral outcome (already vaccinated) rather than parent intentions, as this provides a more objective measure of outcomes. These outcomes were only weakly correlated ($r = 0.22$).

Of the 1300 variables available in the dataset, we selected a mixture of socio-demographic and psychological variables which we believed to be theoretically relevant to pediatric care. We describe these predictors in detail below:

Socio-Demographic factors. Parents reported **age** in years using a set of ranges (18–24, 25–30, 31–35, 36–40, 41–45, 46–50, 56–60, and 60+ years). **Education** was reported in terms of highest degree achieved (Less than high school, some high school, high school diploma/GED, some college, Associate degree, Bachelor's degree, Master's degree, Doctorate or professional degree). **Parent employment status** was aggregated into three categories: Employed (parents reported working full-time, working part-time, working but having hours reduced), Unemployed (parents reported being unemployed or laid off, temporarily out of work or furloughed, unemployed and looking for work, unemployed and not looking for work) or Other (keeping house/raising children, retired, student, and other). Parents were marked has having **lost employment** if they reported being employed before the pandemic and were either unemployed or other at the current report. **Child health insurance** status was aggregated into three categories: Private (parents report private, through current or former employer, direct from insurance company), Public (Medicare, Medigap, Medicaid, CHIP, military-related health care such as TRICARE (CHAMPUS)/VA Healthcare/CHAMP_VA, Indian Health Service, state-sponsored health plan, or other government health plan), or None/Other. We also included whether there was an **infant** in the household (1 – *Yes,* 0 – *No*), the **number of adults** living in the household, and the **number of children** living in the household. For **caregiver race**, parents were allowed to select any of the following: White/Caucasian, Black/African American, American

Indian/Alaskan Native, Asian, Native Hawaiian/Pacific Islander, Other. Parents who selected anything other than White or Black and parents who selected multiple options were categorized as “Other” for the purposes of these analyses. **Caregiver ethnicity** was recorded as Hispanic or Not Hispanic. We also noted whether families were living at or below the federal **poverty** level (1 – *Yes, below the poverty line, 0 – No, above the poverty line)* by comparing their 2019 household income to the poverty level specified for their state and household size. We used self-reported state of residence to estimate the **incidence** (number of new cases per 1000 residents in the past two weeks) and **prevalence** (number of total cases per 1000) of COVID-19 in each parent’s state.

Psychological Factors – Child Temperament. We collected relevant psychological information on children’s well-being by examining levels of fussiness and worry. The items – one per domain – were drawn from the Child Behavior Checklist (Achenbach, 1999). Parents reported how well the items “fussy or defiant” and “too fearful or anxious” described their child using the response options *Not at all* (0), *Somewhat/sometimes true* (1), and *Often/very true* (2).

Psychological Factors – Parent Mental Health. We also gathered psychological data on parents, including well-being and psychosocial characteristics. Specifically, parent mental health was assessed in four categories: anxiety, depression, loneliness, and stress. The items to assess these domains were drawn from the Generalized Anxiety Disorder Screener (Spitzer et al., 2006; two items, correlated $r = 0.81$), the Patient Health Questionnaire-2 (Kroenke et al., 2003; two items, correlated $r = 0.76$) and one item each for loneliness and stress, both of which were created for the study. Parents reported the frequency of these feelings on a scale from 1 (*Never*) to 4 (*Always*).

Psychological Factors – Parent Personality. Parent personality was assessed using the SAPA Personality Inventory (SPI; Condon, 2017), an empirically-derived measure which captures a large number (27) of narrow traits. The SPI measure consists of small item banks for each of the 27 traits. These item banks were identified in prior research, using three samples (combined $N > 125{,}000$) and a sequence of exploratory factor analyses (in multiple samples) and confirmatory factor analysis. As appropriate, these samples – which were large and internationally diverse – were also used in identifying the item response theory (IRT) based item calibrations. This procedure is consistent with those used for similar psychosocial instruments (e.g., PROMIS™; Cella et al., 2010) and results in scores which are normed to the calibration sample. In other words, a score of 1 on a personality trait indicates that the parent scored one standard deviation above the mean *of the calibration sample*, not of the current analysis sample. Item calibrations, as well as additional information regarding the samples used and psychometric properties of the scales, are available in manual cited (Condon, 2017). We used the calibrations identified from this prior research in an IRT-based scoring procedure to estimate trait levels for participants in the current study.

When sampling from item banks such as the ones provided, researchers may choose to administer the same item(s) to each participant or to present them with a random selection of items. We chose to randomly present one of the best three items for each trait, rather than the same item for each participant. Why not choose a more straightforward strategy? A limitation of administering the same item to each participant is that some items in a scale may correlate more strongly or weakly with an outcome than the overall trait, perhaps due to the content of the item or even just the wording. However, if multiple items are administered to the sample, if not an individual participant, then sample-level statistics will more accurately represent the correlation between the full trait and the outcome. (See Supplemental File Figs. S1 and S2 for visualization of this effect: the relationship of individual items to the outcomes are relatively similar within traits in these data).

Parents reported how well each item described them on a scale from 1 (*Very inaccurate*) to 6 (*Very accurate*). Participation in the psychosocial characteristics survey was an optional add-on to the core RAPID-EC survey and was only administered during 5 consecutive weeks, between November 1 and December 3. Each parent only participated in the psychosocial characteristics survey one time.

2.3. Data analysis

The analytic sample included all parents who completed the psychosocial characteristics survey, in addition to completing the regular survey ($N = 1872$). For this sample, we calculated descriptive statistics, stratified by outcome. Next, we sought to identify the most predictive model of each outcome using all variables listed above. We took a machine learning approach to these analyses, to guard against overfitting and develop models with the greatest likelihood of providing utility in other samples. This approach involved several steps:

First, we split our data into training (80%; $N_{wellchild} = 1404$; $N_{flu} = 1368$) and test (20%; $N_{wellchild} = 468$; $N_{flu} = 458$) subsets. Dummy codes were used to represent categorical variables, and all variables were standardized to facilitate interpretation of relative effect size. Using the training set, we ordered the predictors by absolute value of the correlation with the outcome.

Next, we fit to the training data a succession of n logistic lasso regression models; each model contained the top n predictors (ranked by correlation). Lasso models shrink coefficient estimates, encouraging sparse models, which avoid overfitting. These models are commonly used in regression analyses with many predictors (Mõttus et al., 2017; Revelle et al., 2021; Yarkoni and Westfall, 2017). Further protecting against overfitting, model fit was estimated using 10-fold cross validation. Model fit was assessed using the area under the ROC curve, which provides better estimates when classes are unbalanced. These models were fit using complete cases only. In the supplemental material, we report missingness across variables and repeat these analyses using a K-nearest neighbor imputation method.

Finally, we select the model with the greatest fit (highest area under the curve) and fit this final model to the training data. This provides coefficient estimates, which are used to interpret the relative importance of each predictor in the model. The final model is also fit to the holdout (test) dataset, to produce an estimate of model accuracy.

Standardization occurred during the machine learning process as follows: As part of the cross-validation step in the lasso regression models, the training data are partitioned into 10 equal sets using the outcome (e.g., well-child visits) as a stratum (e.g., if 70% of all participants attended a well-child visit, then roughly 70% of participants in each of the 10 sets will have attended a well-child visit). The first nine sets are pooled together. At this point, data cleaning and transformation is applied, including standardization. The model is fit to these pooled data. The model is then tested on the remaining, tenth set, which has been cleaned and transformed separately from the pooled data. The fit of the model to this sample is saved. The process is repeated such that each of the ten sets is held out and tested. After the 10-fold cross validation is completed, the model with the best fit is selected as the final model. This model is then applied to the test dataset. Again, at this step, data transformation is applied. It is important that standardization occurs within each of the folds of the dataset, as standardizing prior to implementing the machine learning algorithms can “contaminate” the data by transferring information (e.g., about averages or spread) from the training data to the test data or from one fold to another.

For these analyses, we replaced the parent age variable with a new variable: young parents, which indicates whether the parent was younger than 25 years of age. Education was treated as a continuous variable ranging from 1 to 8.

2.4. Preregistration

These analyses were preregistered (osf.io/79hxq) and all analysis code is available at osf.io/r348d. (These links will be shortened post-review.) We note here deviations from the preregistration.

First, there is an error in the preregistration, which says that we will use personality collected in May 2020. Personality assessment occurred both during May 2020 and during November/December 2020, but we only used the personality data collected in the fall. For some clarification, it was a different set of parents who provided personality data in May. However, only a portion of them ($N = 182$) continued with the study through the fall and would have been included in the current analyses. We chose to omit them, given the potential for personality to have either changed during these six months or have been influenced by seasonal factors. Second, we used three categories for child insurance, not two (adding None/Other, which accounted for 5% of the sample). Third, we added 2019 vaccination status as a predictor variable in the vaccine regression analyses. We did not preregister the *t*-tests and chi-square tests.

3. Results

3.1. Well-child visits

Table 1 provides the descriptive statistics for our sample, split across well-child visit attendance. We note here the characteristics of parents that were significantly ($p < .05$) associated with well-child visits: Parents who attended well-child appointments during the pandemic were more educated (Cramer's $V = 0.13$), more likely to have private health insurance for their children (Cramer's $V = 0.12$), be employed (Cramer's $V = 0.09$), have only one child (Cramer's $V = 0.16$), identify as non-Hispanic (Cramer's $V = 0.07$), and have income greater than 1.5 times the federal poverty level (Cramer's $V = 0.10$). These parents also reported lower levels of anxiety (Cohen's $d = -0.23$), depression ($d = -0.32$), stress ($d = -0.22$), and loneliness ($d = -0.13$), as well as lower levels of child fussiness ($d = -0.17$) and fearfulness ($d = -0.18$). These parents lived in states with greater prevalence of COVID-19 ($d = 0.09$). In terms of psychosocial characteristics, parents who attended well-child appointments were more sociable ($d = 0.17$), industrious ($d = 0.13$), and emotionally stable ($d = 0.11$), and less introspective ($d = -0.10$) and conservative ($d = -0.11$).

The best fitting logistic model used 30 predictors (Fig. 1A shows fit as measured by area under the curve as a function of the number of variables included in the model). This model had an accuracy of 62.0% in the training data and 62.8% in the test data (Fig. 1B depicts the ROC curves). For binary outcome variables (such as the ones used in the current study), fit generally varies between 50% (guessing) and 100%, although the lower bound of accuracy can be higher if one particular outcome is substantially more likely than the other. We believe that the accuracy for the well-child visits (62%) is certainly better than guessing, but not especially impressive. In the test data, the model R^2 was 0.17. This model suggested the most important variables were the number of children in the household (having fewer children is associated with greater likelihood of going to a well-child visit, *odds ratio* $_{(3\ children)} = 0.74$, $OR_{(2\ children)} = 0.91$) and parent depression ($OR = 0.75$). Additional structural and demographic factors associated with decreased likelihood of attending a well-child visit were being unemployed ($OR = 0.92$) and, surprisingly, educated ($OR = 0.995$), and White caregivers were more likely to attend than Hispanic ($OR = 1.12$). Several psychological factors were among those most important, including parent conservativism ($OR = 0.87$), sociability ($OR = 1.24$), introspection ($OR = 0.87$), well-being ($OR = 0.99$), and child fearfulness ($OR = 0.88$).

Factors are listed in order of importance in Fig. 1C, where bars are used to represent the transformed regression coefficient – represented here as odds ratios – associated with each variable. Odds ratios thus represent the relationship of a variable to well-child visits holding all other variables constant. Regularized models "shrink" small coefficient estimates, resulting in many coefficient estimates equal to 0, which is depicted in this figure as variables with no bars. They were included in this figure to accurately represent the regression model. Predictors were standardized to generate comparable coefficient estimates; the odds ratio indicates the ratio change in likeliness to attend a well-child visit for a one-standard deviation increase in the predictor, holding all other variables constant.

3.2. Flu vaccine

Parents who vaccinated their child against influenza were older (Cramer's $V = 0.12$), more educated (Cramer's $V = 0.27$), more likely to have private health insurance (Cramer's $V = 0.22$), be employed (Cramer's $V = 0.08$), have one or two children (Cramer's $V = 0.09$), have two adults in the household (Cramer's $V = 0.11$), less likely to identify as Black (Cramer's $V = 0.13$), more likely to identify as Hispanic (Cramer's $V = 0.04$), have income greater than 1.5x the federal poverty level (Cramer's $V = 0.18$), and less likely to have lost employment (Cramer's $V = 0.08$). These parents reported lower levels of anxiety ($d = -0.10$), depression ($d = -0.17$), and child fussiness ($d = -0.10$). They lived in area with greater incidence of COVID-19 ($d = 0.12$). In terms of psychosocial characteristics, these parents were more industrious ($d = 0.16$), authoritarian ($d = 0.14$), and perfectionistic ($d = 0.13$) and less impulsive ($d = -0.14$), easy-going ($d = -0.13$) and conservative ($d = -0.15$). The differences in percentile and score are listed in Table 1.

The best fitting logistic model used 14 predictors (see Fig. 2A for fit as a function of the number of variables). This model correctly predicted outcomes 74.7% of the time in the training data and 74.4% of the time in the test data (Fig. 2B depicts the ROC curves), a moderate effect size for prediction. In the test data, the model R^2 was 0.50. Coefficient estimates suggest that the important variables are a mix of social and demographic factors, as well as parent psychosocial characteristics. In accordance with prior work (Sokol and Grummon, 2020), the biggest predictor was past behavior: children were more than twice as likely to be vaccinated this season if they had been vaccinated last year ($OR = 2.65$). In addition, parents were more likely to vaccinate if they had private insurance ($OR = 1.17$), were more educated ($OR = 1.26$), were employed ($OR = 0.86$), and lived in an area with greater COVID incidence ($OR = 1.20$). Like attending well-child visits, parents were also more likely to attend if they were more industrious ($OR = 1.05$) and more compassionate ($OR = 1.11$). All variables are listed in order of importance in Fig. 2C.

4. Discussion

Parents' adherence to recommend well-child visits and vaccinations during fall 2020 were associated with a mix of social, demographic, and psychosocial characteristics. These models highlight several ways – individual and systemic – in which the pediatric healthcare system could be adapted to better serve communities.

Importantly, we also found that pediatric care and vaccination decisions were driven as much by parental psychosocial characteristics as by structural and demographic factors. We note that the effect sizes for psychological characteristics were modest (e.g., a Cohen's *d* of 0.2 for many in the paired-samples *t*-tests); however, the expected relationship between psychological measures and specific real-world behaviors is generally modest, but can compound into more substantial effects over time (Funder and Ozer, 2019). For example, a parent who misses a single well-child visit is likely to miss several, and the child is at greater risk for developing health problems in adolescence which could contribute to long-lasting health disparities over the lifetime.

Notable psychosocial characteristics associated with pediatric care involve attitudes (conservatism), matching prior work (Baumgaertner et al., 2018), suggesting that parents' political and cultural beliefs have a direct impact on their health care choices. Other traits – notably easy-goingness and industry – suggest that the current pediatric health care system may be only accessible to a subset of caregivers. Our findings suggests that adequate pediatric care is a reward for parents who are above average in industriousness or achievement-striving. Instead of a system that requires substantial work on the part of parents, pediatric clinics might seek to reduce barriers to care, especially in terms of minimizing the amount of effort needed to receive care. From a public

Table 1
Descriptive statistics stratified by well-child appointment adherence and child vaccination. Table reports either counts and percentages (in the case of categorical variables) or means and 95% confidence intervals (in the case of continuous variables). Categorical variable differences are tested using chi-square tests of independence. Differences in continuous variables are tested with independent-samples *t*-tests. *ES* = effect size (Cramer's *V* for chi-square tests, Cohen's *d* for *t*-tests).

	Well-child Appointment				Child influenza vaccine			
	Missed (N = 588)	Attended (N = 1284)	*p*	*ES*	Did not vaccinate (N = 837)	Vaccinated (N = 989)	*p*	*ES*
Age			.833	.06			**.006**	.12
N-Miss	1	8			4	4		
18-24	21 (3.6%)	40 (3.1%)			35 (4.2%)	22 (2.2%)		
25-30	135 (23.0%)	306 (24.0%)			228 (27.4%)	201 (20.4%)		
31-35	217 (37.0%)	509 (39.9%)			312 (37.5%)	406 (41.2%)		
36-40	160 (27.3%)	302 (23.7%)			192 (23.0%)	258 (26.2%)		
41-45	44 (7.5%)	99 (7.8%)			53 (6.4%)	81 (8.2%)		
46-50	7 (1.2%)	11 (0.9%)			7 (0.8%)	11 (1.1%)		
51-55	1 (0.2%)	4 (0.3%)			2 (0.2%)	3 (0.3%)		
56-60	1 (0.2%)	3 (0.2%)			2 (0.2%)	2 (0.2%)		
61+	1 (0.2%)	2 (0.2%)			2 (0.2%)	1 (0.1%)		
Education			**.004**	.13			**< .001**	.27
N-Miss	44	73			53	51		
Less than high school	5 (0.9%)	1 (0.1%)			4 (0.5%)	1 (0.1%)		
Some high school	4 (0.7%)	12 (1.0%)			9 (1.1%)	5 (0.5%)		
High school diploma/GED	61 (11.2%)	89 (7.3%)			96 (12.2%)	49 (5.2%)		
Some college	109 (20.0%)	220 (18.2%)			202 (25.8%)	120 (12.8%)		
Associate degree	51 (9.4%)	104 (8.6%)			83 (10.6%)	68 (7.2%)		
Bachelor's degree	179 (32.9%)	413 (34.1%)			237 (30.2%)	349 (37.2%)		
Master's degree	112 (20.6%)	296 (24.4%)			139 (17.7%)	261 (27.8%)		
Doctorate or professional	23 (4.2%)	76 (6.3%)			14 (1.8%)	85 (9.1%)		
Child Insurance			**< .001**	.12			**< .001**	.22
N-Miss	1	2			1	1		
None/Other	41 (7.0%)	57 (4.4%)			61 (7.3%)	30 (3.0%)		
Private	319 (54.3%)	835 (65.1%)			419 (50.1%)	710 (71.9%)		
Public	227 (38.7%)	390 (30.4%)			356 (42.6%)	248 (25.1%)		
Employment			**<.001**	.09			**< .001**	.08
Employed	290 (49.3%)	726 (56.5%)			406 (48.5%)	587 (59.4%)		
Other	127 (21.6%)	283 (22.0%)			200 (23.9%)	201 (20.3%)		
Unemployed	171 (29.1%)	275 (21.4%)			231 (27.6%)	201 (20.3%)		
Infant/toddler in household			.181	.00			.488	.03
N-Miss	20	37			28	29		
Infant/toddler in household	463 (81.5%)	1048 (84.0%)			671 (82.9%)	808 (84.2%)		
No infant/toddler	105 (18.5%)	199 (16.0%)			138 (17.1%)	152 (15.8%)		
Number of children in household			**<.001**	.16			**< .001**	**.09**
N-Miss	88	100			115	70		
1	150 (30.0%)	537 (45.4%)			274 (38.0%)	397 (43.2%)		
2	212 (42.4%)	459 (38.8%)			277 (38.4%)	377 (41.0%)		
3+	138 (27.6%)	188 (15.9%)			171 (23.7%)	145 (15.8%)		
Number of adults in household			.573	.03			**< .001**	.11
N-Miss	1	1			1	1		
1	66 (11.2%)	128 (10.0%)			115 (13.8%)	73 (7.4%)		
2	459 (78.2%)	1030 (80.3%)			625 (74.8%)	832 (84.2%)		
3+	62 (10.6%)	125 (9.7%)			96 (11.5%)	83 (8.4%)		
race			.208	.05			**< .001**	.13
Black	70 (11.9%)	119 (9.3%)			115 (13.7%)	68 (6.9%)		
Other	55 (9.4%)	128 (10.0%)			63 (7.5%)	116 (11.7%)		
White	463 (78.7%)	1037 (80.8%)			659 (78.7%)	805 (81.4%)		
ethnicity			**<.001**	.07			**.028**	.04
N-Miss	17	38			18	15		
Hispanic/Latinx	98 (17.2%)	140 (11.2%)			123 (15.0%)	112 (11.5%)		
Not Hispanic	473 (82.8%)	1106 (88.8%)			696 (85.0%)	862 (88.5%)		
Household income (2019)			**.001**	.10			**< .001**	.18
Below 1.5 x FPL	169 (29%)	418 (71%)			271 (32%)	566 (68%)		
Above 1.5 x FPL	281 (22%)	1002 (78%)			165 (17%)	823 (83%)		
Lost employment			.232	.05			**.005**	.08
N-Miss	201	436			297	328		
Yes	79 (20.4%)	149 (17.6%)			117 (21.7%)	102 (15.4%)		
No	308 (79.6%)	699 (82.4%)			423 (78.3%)	559 (84.6%)		
Influenza vaccine in 2019–2020 season								
N-Miss					35	13	**<.001**	1.10
Vaccinated					340 (42.4%)	857 (87.8%)		
Not vaccinated					462 (57.6%)	119 (12.2%)		
Parent anxiety	1.32 (1.24, 1.39)	1.08 (1.03, 1.13)	**<.001**	-.23	1.20 (1.14, 1.26)	1.11 (1.05, 1.17)	**.035**	-.10
Parent depression	1.06 (0.98, 1.13)	0.74 (0.69, 0.78)	**<.001**	-.32	0.91 (0.85, 0.97)	0.77 (0.72, 0.82)	**< .001**	-.17
Parent stress	2.38 (2.28, 2.48)	2.06 (1.99, 2.13)	**<.001**	-.22	2.22 (2.13, 2.31)	2.11 (2.03, 2.19)	.062	-.09
Parent loneliness	2.10 (2.02, 2.19)	1.89 (1.83, 1.94)	**<.001**	-.13	2.00 (1.93, 2.07)	1.91 (1.85, 1.98)	.077	-.08
Child fussiness	1.09 (1.04, 1.15)	0.99 (0.96, 1.02)	**.001**	-.17	1.06 (1.01, 1.10)	0.99 (0.95, 1.03)	**.032**	-.10
Child fearfulness	0.60 (0.55, 0.66)	0.45 (0.42, 0.48)	**<.001**	-.18	0.49 (0.45, 0.54)	0.49 (0.45, 0.53)	.859	-.00

(*continued on next page*)

Table 1 (*continued*)

	Well-child Appointment				Child influenza vaccine			
	Missed (N = 588)	Attended (N = 1284)	*p*	*ES*	Did not vaccinate (N = 837)	Vaccinated (N = 989)	*p*	*ES*
COVID incidence (two week, per 1000)	0.49 (0.47, 0.51)	0.51 (0.49, 0.52)	.214	.05	0.49 (0.47, 0.51)	0.52 (0.51, 0.54)	**.010**	.12
COVID prevalence (per 1000)	33.64 (32.60, 34.68)	34.96 (34.23, 35.69)	**.043**	.09	34.68 (33.80, 35.56)	34.86 (34.02, 35.70)	.772	.01
Compassion	0.11 (0.01, 0.20)	0.18 (0.12, 0.24)	.177	.07	0.09 (0.01, 0.17)	0.22 (0.16, 0.28)	**.008**	.13
Irritability	−0.48 (−0.52, −0.43)	−0.51 (−0.55, −0.48)	.233	-.05	−0.51 (−0.55, −0.48)	−0.49 (−0.53, −0.46)	.415	.04
Sociability	0.74 (0.64, 0.83)	0.95 (0.88, 1.02)	**<.001**	.17	0.82 (0.74, 0.91)	0.92 (0.84, 1.00)	.111	.08
Well-being	0.76 (0.73, 0.80)	0.86 (0.84, 0.88)	**<.001**	.23	0.80 (0.77, 0.83)	0.85 (0.83, 0.88)	**.007**	.13
Sensation-Seeking	−0.74 (−0.84, −0.64)	−0.78 (−0.84, −0.73)	.431	-.04	−0.73 (−0.81, −0.66)	−0.82 (−0.88, −0.75)	.086	-.08
Anxiety	0.16 (0.06, 0.25)	0.02 (−0.05, 0.09)	**.027**	-.10	0.02 (−0.07, 0.10)	0.10 (0.03, 0.18)	.133	.07
Honesty	3.41 (3.32, 3.50)	3.31 (3.24, 3.37)	.081	-.08	3.38 (3.30, 3.46)	3.30 (3.23, 3.38)	.152	.07
Industry	0.11 (0.01, 0.21)	0.27 (0.21, 0.34)	**.006**	.13	0.12 (0.03, 0.20)	0.31 (0.23, 0.38)	**< .001**	.16
Intellect	0.30 (0.21, 0.38)	0.25 (0.19, 0.31)	.414	-.05	0.26 (0.18, 0.34)	0.28 (0.21, 0.35)	.767	.01
Creativity	−0.30 (−0.40, −0.19)	−0.40 (−0.47, −0.33)	.120	-.08	−0.32 (−0.42, −0.23)	−0.40 (−0.48, −0.32)	.225	-.06
Impulsivity	−0.25 (−0.35, −0.14)	−0.26 (−0.33, −0.19)	.828	-.02	−0.17 (−0.26, −0.08)	−0.34 (−0.42, −0.26)	**.004**	-.14
Attention-Seeking	−2.01 (−2.14, −1.88)	−1.96 (−2.05, −1.87)	.567	.02	−1.98 (−2.09, −1.87)	−1.98 (−2.08, −1.88)	.969	.00
Order	0.50 (0.44, 0.56)	0.57 (0.53, 0.61)	.065	.09	0.52 (0.47, 0.57)	0.57 (0.52, 0.62)	.152	.07
Authoritarianism	0.32 (0.25, 0.40)	0.37 (0.32, 0.42)	.253	.07	**0.29 (0.23, 0.36)**	**0.41 (0.36, 0.47)**	**.003**	.14
Charisma	0.21 (0.11, 0.30)	0.17 (0.10, 0.23)	.480	-.03	0.22 (0.14, 0.30)	0.14 (0.06, 0.21)	.146	-.07
Trust	0.08 (−0.02, 0.18)	0.18 (0.11, 0.25)	.106	.08	0.09 (0.01, 0.18)	0.20 (0.12, 0.28)	.072	.08
Humor	−0.44 (−0.53, −0.34)	−0.39 (−0.45, −0.32)	.379	.05	−0.40 (−0.48, −0.32)	−0.40 (−0.46, −0.33)	.911	.00
Emotional-Expressiveness	0.27 (0.17, 0.38)	0.28 (0.21, 0.35)	.932	.00	0.26 (0.17, 0.35)	0.27 (0.19, 0.35)	.903	.00
Art-Appreciation	2.46 (2.35, 2.58)	2.38 (2.30, 2.46)	.262	-.07	2.45 (2.35, 2.55)	2.38 (2.29, 2.47)	.280	-.05
Introspection	−0.70 (−0.79, −0.61)	−0.82 (−0.88, −0.75)	**.042**	-.10	−0.76 (−0.83, −0.68)	−0.80 (−0.87, −0.73)	.424	-.04
Perfectionism	−0.09 (−0.18, −0.00)	−0.01 (−0.07, 0.04)	.141	.09	−0.11 (−0.18, −0.04)	0.03 (−0.04, 0.09)	**.006**	.13
Self-Control	0.04 (−0.05, 0.13)	0.04 (−0.02, 0.09)	.980	.00	0.02 (−0.06, 0.09)	0.05 (−0.01, 0.12)	.466	.03
Conformity	0.62 (0.55, 0.70)	0.67 (0.62, 0.72)	.294	.06	0.65 (0.58, 0.71)	0.67 (0.61, 0.72)	.706	.02
Adaptability	−0.15 (−0.30, 0.01)	−0.24 (−0.34, −0.13)	.351	-.05	−0.12 (−0.25, 0.01)	−0.29 (−0.40, −0.17)	.053	-.09
Easy-Goingness	−0.20 (−0.28, −0.13)	−0.28 (−0.33, −0.23)	.085	-.08	−0.20 (−0.26, −0.13)	−0.32 (−0.38, −0.26)	**.005**	-.13
Emotional-Stability	−1.98 (−2.09, −1.86)	−1.80 (−1.88, −1.73)	**.016**	.11	−1.93 (−2.03, −1.83)	−1.80 (−1.89, −1.71)	.051	.09
Conservatism	−1.75 (−1.89, −1.61)	−1.93 (−2.03, −1.84)	**.028**	-.11	−1.75 (−1.86, −1.63)	−2.01 (−2.12, −1.90)	**.001**	-.15

health standpoint, these findings suggest interventions should seek to reduce the work or organization needed to receive pediatric care. For example, prior work suggests that vaccination rates benefit from functional proximity, rather than base proximity (Beshears et al., 2016); in other words, people take advantage of opportunities they come across naturally, even if those opportunities are physically farther away. Similar to the use of retail locations for adult vaccinations (Mehrotra et al., 2008), there may be benefits to vaccinating in alternative locations frequented by parents of young children, such as daycare centers and public parks. It appears that telehealth services have already made strides in this area, as they reduce the need to find transportation, childcare, and additional time off work to attend the visit (Marcin et al., 2016), although this method of care is not without its limitations (Haimi et al., 2018). However, we also note that traits like easy-goingness and industry may influence pediatric preventive care through other or additional mechanisms, such as attitudes towards health care. This would suggest that interventions aimed at changing parents' behaviors – perhaps through highlighting the importance of pediatric care – would be the most effective.

Parental personality traits may be used to improve pediatric preventive care in other ways. Personality traits can be used to identify potential candidates for interventions or tailor intervention messaging or programs to fit with participants' unique strengths and weaknesses (Boersma et al., 2011; Chapman et al., 2011; Condon et al., 2017; Hagger-Johnson and Pollard Whiteman, 2008). Importantly, patient (and presumably, parent) personality can be assessed through observer-report (Israel et al., 2014), rather than self-report, which reduces the burden on patients while enriching the information available to physicians.

Several of the demographic variables that were significantly associated with well-child visits and flu vaccinations suggest that structural barriers prevent parents from adhering to recommended pediatric care schedules during the pandemic. These correlates largely paint a picture of limited resources: financial, informational, and time-based. Consistent with prior work (Sokol and Grummon, 2020), parents living above the federal poverty line were more likely to attend a visit and vaccinate their child. Across outcomes, parent education level and child insurance status were large, unique predictors. We note that parent race and ethnicity remained significant predictors of outcomes after controlling for poverty status, suggesting that inequities in care are not simply a result of differences in income. While the current analyses cannot speak to the mechanisms driving these differences, we note communities of color experience structural inequities in access to health care (Johnson, 2020) and have greater distrust in the medical system (Halbert et al., 2006), justified given the documented discrimination and abuse of these communities (Washington, 2006). And finally, a major factor facilitating well-child visits was having fewer children. Future research should examine the role of childcare providers in enabling parents to seek

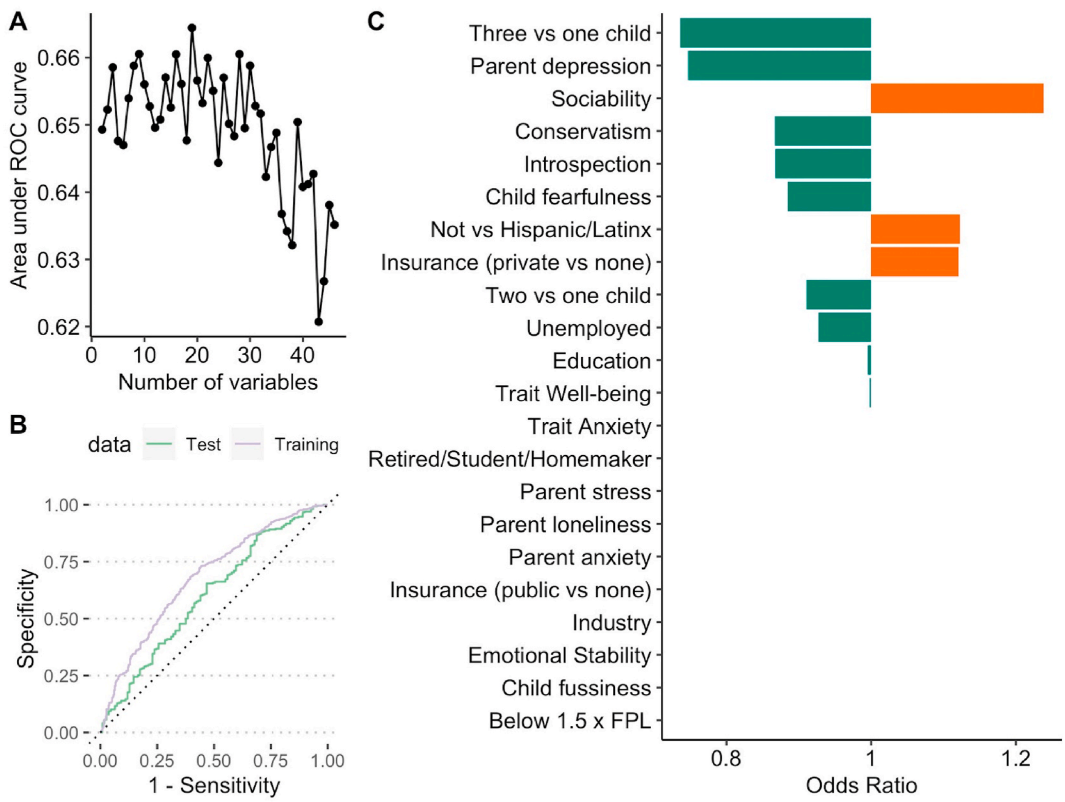

Fig. 1. Results from lasso logistic regression analyses of well-child visits. **A.** Area under the ROC curve as a function of the number of variables in the model; a model that performs no better than guessing has an area of 0.50; larger areas indicate more predictive models. **B.** ROC curves of the final model in both the training and test sets. A dashed line represents the baseline model (random guessing), and curves above this line indicate better prediction. **C.** Variable importance in the final model. Odds ratios represent change in odds of not missing a well-child appointment for every one-standard deviation increase in the predictor. Odds greater than one indicate increases on this variable are associated with a greater likelihood of making an appointment, while odds less than one indicate less likelihood.

primary pediatric care.

Despite the relatively modest correlation between the two outcomes, well-child visits and flu vaccines, they shared several significant predictors. Parents who kept up with well-child appointments and vaccinated their children were more educated and employed, had private insurance and fewer children, identified as non-Hispanic, had better mental health, and were more industrious and less conservative. These findings collectively suggest that pediatric preventive care is associated with greater resources (including financial, time, and ability) and better outcomes overall, and this conclusion is relatively unsurprising. On the flip side, there were some factors which were unassociated with either outcome – notably self-control– which we may have expected to be relevant given prior associations with adherence (Hill and Roberts, 2011). We propose that more specific measures would be appropriate for such findings, such as having self-control *to stick with one's appointments*.

Some factors were unique predictors of one or the other outcome. Well-child visits were uniquely associated with less loneliness, more sociability, lower stress, and lower anxiety. This may suggest that parents were more able to make well-child visits when they were experiencing greater social and emotional well-being, or perhaps parents receive a boost in these psychological factors through interacting with their pediatricians. Factors uniquely associated with flu vaccines are thought to represent more specific healthcare processes. For example, flu vaccines were uniquely associated with authoritarianism, which we found surprising, given that this trait is generally associated with conservatism (Condon, 2017). However, authoritarianism is generally related to rule-following, so these parents may be more likely to follow specific guidance, like the CDC vaccine schedules. Vaccines were also associated with perfectionism; interestingly, this trait represents a combination of conscientiousness and anxiety, and so this relationship would be consistent with a theory that anxiety leads to beneficial health behaviors (Friedman, 2000).

There were a number of psychological variables unassociated with well-child visits or vaccines, suggesting these variables are relatively unimportant for pediatric preventive care. For the most part, it is unsurprising that these variables – e.g., art appreciation, humor, and charisma – were unassociated with care, although there were exceptions. For example, it may be surprising that parent self-control was not associated with either outcome, especially given the significant attention paid to self-control and health outcomes in the literature (e.g., Moffitt et al., 2011). Similarly, we may have expected to see trust reach significance, given the importance of trust in institutions specifically to healthcare (Baumgaertner et al., 2018; Halbert et al., 2006). However, we note that in both cases, there may be a mismatch between a general experience and the specific construct measured. For example, self-control may be specific to eating behavior, not health generally, and trust in medicine is more specific than trust in general.

Future work will be required to determine whether the associations identified in the current study will generalize outside the pandemic context, especially between personality traits and pediatric care. One possibility is that the personality-outcomes relationships are unaffected by situation, as has been found in a recent mega-analysis related to health outcomes (Beck, 2020). On the other hand, personality may have the largest effect during periods of massive social upheaval (Caspi and Moffitt, 1993), which may be how some characterize the COVID-19 pandemic. Or perhaps the answer is more nuanced, and some trait-outcome relationships are stable while others are heightened by situational constraints(e.g., Siritzky et al., 2021). We believe the associations of care with parental industry are likely to remain for as long as some degree of conscientiousness is required to navigate the health care

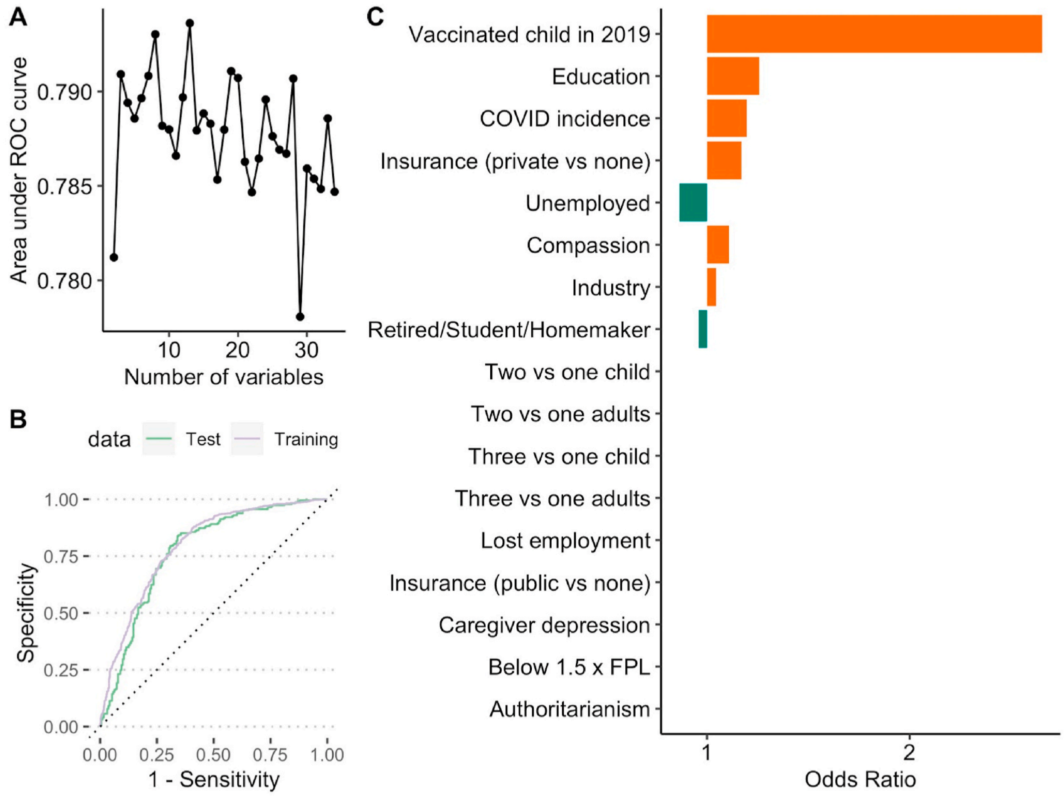

Fig. 2. Results from lasso logistic regression analyses of 20–21 child influenza vaccination. **A.** Area under the ROC curve as a function of the number of variables in the model; a model that performs no better than guessing has an area of 0.50; larger areas indicate more predictive models. **B.** ROC curves of the final model in both the training and test sets. A dashed line represents the baseline model (random guessing), and curves above this line indicate better prediction. **C.** Variable importance in the final model. Odds ratios represent change in odds of vaccinating children for every one-standard deviation increase in the predictor. Odds greater than one indicate increases on this variable are associated with a greater likelihood of vaccinating a child, while odds less than one indicate less likelihood.

system. However, some associations may reflect culturally specific processes; for example, conservatism may have represented some politization of vaccines and health care specific to the current pollical climate.

Importantly, the current analyses did not distinguish between preventive care behaviors at different stages of infant and child development. The periodicity schedule published by the American Association of Pediatrics recommends frequent visits during infancy and a reduction in preventive care through early childhood. Future research should seek to understand whether psychological factors identified here equally facilitate care for children at all stages of early development. These analyses are outside the scope of the current study, as they require greater sample sizes; however, we attempted to limit potential confounds using infant and child covariates.

A limitation of the current research is that the observational nature of data collection combined with a relatively brief assessment period limit opportunities for disentangling the true causal mechanisms from spurious associations. However, we note that, regardless of causal direction, the parent characteristics that are correlated with missing well-child visits and missed vaccinations carry important information. "Risk factors" are like symptoms, pointing researchers and policy makers towards the subpopulations with greatest need of attention and suggesting avenues for further investigation. Future research should seek to understand how relationships between pediatric health behaviors and parent psychosocial characteristics manifest. In addition, the current sample is primarily mothers (96% identify as female). Future research would benefit from the consideration of both mothers' and fathers' personalities and mental health and potentially the interaction of these individual differences in two-parent households.

The use of the lasso-logistic regression paired with cross-validation for model selection has many of the same limitations as more traditional regression models. Specifically, these models are biased to the extent they exclude meaningful causal predictors and include predictors which have non-linear relationships with outcomes. However, it is our belief that the methods used herein are more robust than more traditional analyses in that they guard against overfitting and include assessment of out-of-sample fit.

5. Conclusion

Pediatric care during the COVID-19 pandemic is associated with both structural barriers to care as well as parent characteristics, including parent psychosocial characteristics. Interventions aimed at increasing adherence to well-child visits and pediatric vaccinations should consider both these macro- and individual-level influences.

Declaration of competing interest

The authors have no conflicts of interest to disclose.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.socscimed.2021.114356.

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