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# Utilizing Mixed Graphical Network Models to Explore Parent Psychological Symptoms and Their Centrality to Parent Mental Health in Households with High Child Screen Usage

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## Title

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## Abstract

Especially among adolescents, screens are being used more than ever. In conjunction with this trend, mental illness is increasingly prevalent among both adults and children, and parental psychological problems are shown to be associated with children's TV watching, video watching, and gaming (Pulkki-Råback et al., 2022). This study aims to approach parent mental illness symptom by symptom to explore which specific symptoms are most central to parent psychological problems in households where children show high screen time behaviors. We draw from the Adolescent Brain Cognitive Development Study (ABCD Study®), a nationwide sample of 11,875 children aged 10-13 collected by the National Institute of Mental Health. We utilize Mixed Graphical Models (MGMs) on both polychoric and dichotomized data, using the Extended Bayesian Information Criterion to choose the best models. Within our polychoric data, we pinpoint "I feel worthless and inferior" as a symptom with both high bridge betweenness and strength between symptom communities within high screen time household networks. This symptom also has very high individual node strength and expected influence. Furthermore, we observe that "I lack self-confidence" greatly influences "I feel worthless and inferior" and has a higher normalized accuracy. Within binary high child screen time networks, we find "I have trouble making decisions" as a parent symptom with high bridge strength and betweenness that is central to the overall structure of the network. We compare low and high child screen time networks built from dichotomized parent psychological symptoms to find that ½ of the edges that differ between networks involve the symptom "I feel that I can't succeed." We interpret our polychoric and binary networks to warrant further exploration of the relationship between parents feeling worthless and inferior and that they lack self-confidence in households where children show high screen behaviors. We further conclude that parents feeling like they have trouble making decisions is central to parent psychological problems in high child screen time binary networks. Finally, we believe our approach could be more successfully applied to other psychological datasets with more nonzero responses to parent psychological symptoms to further illuminate parent symptoms that are important in households with high child screen time. Our analyses do not establish causality because our data is cross-sectional.

## Introduction

Across the US, screens are becoming increasingly prevalent in children's lives. In children aged 11 years and younger, 88% of parents say their child uses or interacts with a TV (Nadeem, 2020). While screen usage is rising, screens are increasingly used for child development (Paulich et al., 2021). From TV shows to YouTube, children are influenced by the content they view on screens. For example, research has shown that TV screen time in adolescents increases rule-breaking behavior by 5.9%, social problems by 5%, aggressive behavior by 4%, and thought problems by 3.7% (Guerrero et al., 2019). Moreover, mature video game screen time is shown to decrease sleep duration while increasing somatic complaints and aggressive behavior (Guerrero et al., 2019). Excluding time spent on screens for school and homework purposes, the American Academy of Child and Adolescent Psychiatry (AACAP) recommends a maximum of two hours of screen time a day for children ages 6 to 17. For most children, this recommendation is frequently exceeded. The AACAP estimates that children ages 8 to 12 spend an average of 4-6 hours per day using screens recreationally. Excessive screen time in adolescent age groups has been shown to be correlated with cognitive, behavioral, and emotional disorders while also having the potential to increase risks of early-onset dementia later in life (Neophytou et al., 2021). Given this, screen time is a behavioral variable with far-reaching implications for adolescent mental health.

Mental health problems impact more than 25% of people throughout their lifetimes and these mental health symptoms and diagnoses impact more than just the individual diagnosed. The World Health Organization (WHO) estimates that one in four families has at least one member with a mental health or behavioral disorder. Not only does screen time correlate with adolescent mental health, but so do parent mental illnesses. Parent mental illness has been shown to impact child behavior, social and emotional competence, and sleep patterns (Smith, 2004). Associations between child screen time and child behavioral changes have been studied and the relationship between parent mental illness and their children's screen behaviors is just beginning to be explored (Pulkki-Råback et al., 2022). Parent psychological problems were associated with children's TV watching, video watching, and gaming but not with children's use of social media.

Given the importance of understanding mental illness and its impact on adolescent development and behavior, investigating the relationship between parent psychological problems and their children's screen behaviors could shed light on parenting while suffering from a psychological disorder. If we could identify specific parent psychological conditions or symptoms central to psychological problems in parents whose children have high screen time, there could be implications for how we understand parent-child relationships when parents are mentally ill. Parent-child relationships have even been shown to mediate the negative effects of excessive child screen time (Zhao et al., 2018). Furthermore, a study done in South Africa shows parents believe they have the most impact on their children's development at a median age of 12 years old (Worthman et al., 2016). Parents stated that during their children's early teens, they felt they had the most influence to protect their children from potential powerful ecological risks like substance use and abuse, pregnancy, and violence that emerge during adolescence. Given that parents feel the years around 12 years old are critical in child development, we aim to observe how parent mental illness symptoms interact when their children's screen time is high. This study examines relationships between child reports of their own screen time and parent reports of their own psychological symptoms in a large and diverse nationwide sample of 10 to 13-year-old children collected by the Adolescent Brain Cognitive Development (ABCD) Study run by the National Institute of Mental Health (Garavan et al., 2018). Utilizing this sample of young adolescents, we aim to observe child behavioral and parent psychological relationships at an early stage of development.

While focusing on children in early adolescence, we approach the exploration of parent mental illness in a novel way. Utilizing psychological networks, we draw relationships directly from the ABCD data itself. Psychological networks give the ability to explore particular nodes or symptoms and how they influence other nodes. Past research has shown that we can interpret which symptoms are the most important to the overall picture of mental health by looking at how central a symptom is within our psychological networks and furthermore, we might be able to pinpoint specific symptoms for diagnosis and treatment of psychological disorders. Psychological networks can be interpreted to directly study symptoms that are affecting each other rather than relationships caused by an unobserved latent entity (Epskamp & Fried, 2018). Thus, we examine the network strength and reliability of specific parent psychological symptoms in households with differing child screen behavior, hypothesizing that individual symptoms and categories of symptoms will be stronger in groups of parents who have children with high screen time versus lower screen time.

# Methods

## Data

The ABCD Dataset is the largest longitudinal study of brain development and child and adolescent health in the US. The study is taking place in 21 different research sites across the US and studies 11,875 children all aged 9 to 10 in the first year of the study. These 21 research sites were chosen based on the demographic makeup of nearby schools in the hopes of including all demographic groups. While originally the dataset was focused on substance use in adolescents and which factors impacted substance use as children aged, the dataset broadened to include behavioral and psychological measures, physical wellness and vital signs, cognitive function, environmental factors, and structural and functional brain imaging in addition to biomarkers and genetic assays (Garavan et al., 2018). Baseline data was first collected in Oct 2018 and subsequent follow-ups have and will happen annually for 10 years. As of February 2023, four years of data are available. Through questionnaires, children and parents self-reported measures of behavioral and psychological characteristics, physical wellness, cognitive function, and environmental factors (Saragosa-Harris et al., 2022). The entire dataset contains 52.1% males and 47.8% females.

## Data Preprocessing

Participants were chosen from the 11,875 children participating in the Adolescent Brain Cognitive Development (ABCD) study. In accordance with the institutional review board at the University of California San Diego, anonymous ABCD responses are not subject to their own human subject approval. The data collected in the ABCD study is owned by the National Institute of Mental Health Data Archive and qualified research requests can be placed on their website.

The overall sample is 52% White, 20.3% Hispanic, 15% Black, 2.1% Asian, and 10% Other of Prefer Not to Respond. The sample consists of a fairly upper-middle class socioeconomic bracket with 3.6% of families participating reporting annual family income <$5000; 3.6% reported $5000–$11,999;

2.3% reported $12,000–$15,999; 4.4% reported $16,000–$24,999; 5.5% reported $25,000–$34,999; 7.9% reported $35,000–$49,999; 12.6% reported $50,000–$74,999; 13.2% reported $75,000–$99,999; 27.9% reported $100,000–$199,999; 10.5% reported $200,000+; with 4.3% refused to answer and 4.2% didn't know (Paulich et al., 2021).

We divided the study into two cohorts based on screen time recommendations from the American Academy of Child and Adolescent Psychiatry (AACAP). The low screen time cohort contains children whose average screen time (both weekday and weekend) was under two hours per day, as recommended by the AACAP. The high screen time cohort contains children whose screen time is greater than six hours per day on average. Since the AACAP estimates children aged 8-12 years old spend 4-6 hours per day using screens, our high screen time cohort grouped children who spent more time than the high end of the AACAP average estimate. The ABCD Study asked screen time questions of children at their baseline assessment and during each following year however, parent psychological symptom questionnaires were only collected in the 2-year follow-up assessments. Thus, we are using child screen data and parent mental illness questionnaire data from the 2-year follow-up assessments only.

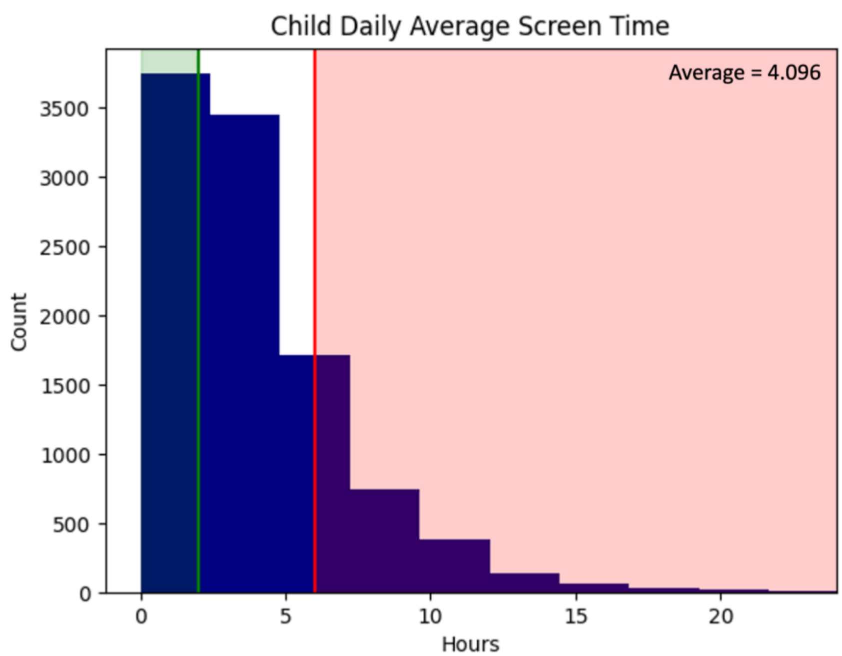



Figure 1. Histogram of children's daily average screen usage. The green line represents the threshold for the low screen time cohort, marking the recommended limit for recreational screen use in children aged 6-17. The light green box represents the low screen time cohort. The red line represents the high end of the AACAP estimated average screen time for 8-12-year-olds. The red box represents the high screen time cohort. These daily average screen times are based on children's estimations of their own screen usage and we credit the extremely high average screen times to children estimating their own screen usage poorly.

Screen time questions were asked in six subcategories and separately for weekdays and weekends. These categories include tv and movie screen time, YouTube and other video screen time, video game screen time, texting screen time, social networking screen time, and video chatting screen time. These screen times are heavily skewed toward tv shows and movies, videos, and video game screen time. Children showed medians of 7 hours of tv show and movie screen time per week, 3.5 hours of YouTube and other videos, 4 hours of video games, 0 hours of texting, 0 hours of social networking, and

0 hours of video chatting per week. To best represent screen time as a whole, we chose to combine the differing screen times into daily average screen usage. This includes screen times from both weekdays and weekends.

Because of the 52% increase in adolescent screen time during the COVID-19 pandemic, we chose to remove data collected during the pandemic (Madigan et al., 2022).

We take an item-level approach to specific parent psychological symptoms and their centrality to mental illness in high and low screen time households. Specifically, we examine 18 specific parent symptoms. These 18 specific symptoms represent the brief problem monitor (BPM) questions that serve as a smaller subsection of the Achenbach System of Empirically Based Assessment (ASEBA) Adult Self Report (ASR) questions asked of parents during their second follow-up visit (de Vries et al., 2020). The BPM questions fall into three categories: internalizing, externalizing, and attention. ASR and BPM responses showed high correlations ($r > 0.88$) and good clinical classification concordance (0.61–0.80) (de Vries et al., 2020). Out of 10,414 parent responses, we found only 57 instances where parents had not responded (shown as NaNs in the ABCD data). We removed these null responses from our sample.

| Attention | Internalizing | Externalizing |
|---|---|---|
| TCONC: "I have trouble concentrating or paying attention for long" | FWRTH: "I feel worthless and inferior" | IMPUL: "I am impulsive or act without thinking" |
| TPLAN: "I have trouble planning for the future" | LCONF: "I lack self-confidence" | CHBEH: "My behavior is very changeable" |
| FFINI: "I fail to finish things I should do" | NLIKE: "I am not liked by others" | TEMPR: "I have a hot temper" |
| WPERF: “My work performance is poor", | TPLAN: "I have trouble making or keeping friends" | THURT: "I threaten to hurt people" |
| TRPIO: "I have trouble setting priorities" | UNHAP: "I am unhappy, sad, or depressed" | UPSET: "I get upset too easily" |
| TDECM: "I have trouble making decisions" | CNSUC: "I feel that I can't succeed" | IMPAT: "I am too impatient" |

Table 1. Brief problem monitor (BPM) five letter codes and symptoms grouped into attention, internalizing, and externalizing categories.

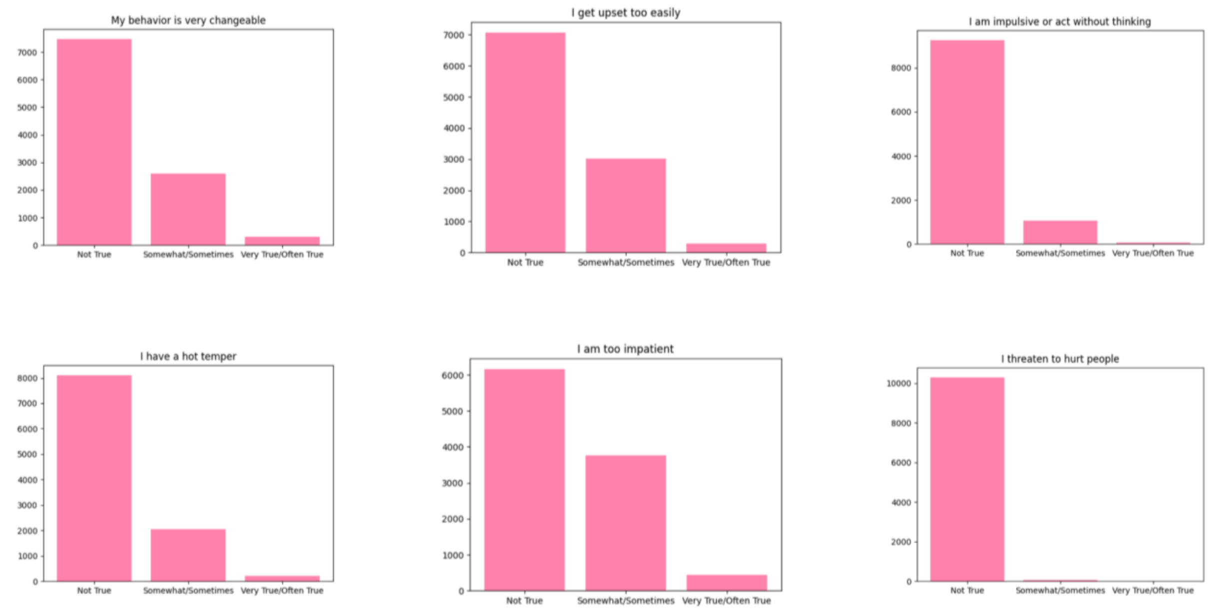



Figure 2. Externalizing symptom responses for the entire cohort (n=10,414 after null responses are removed).

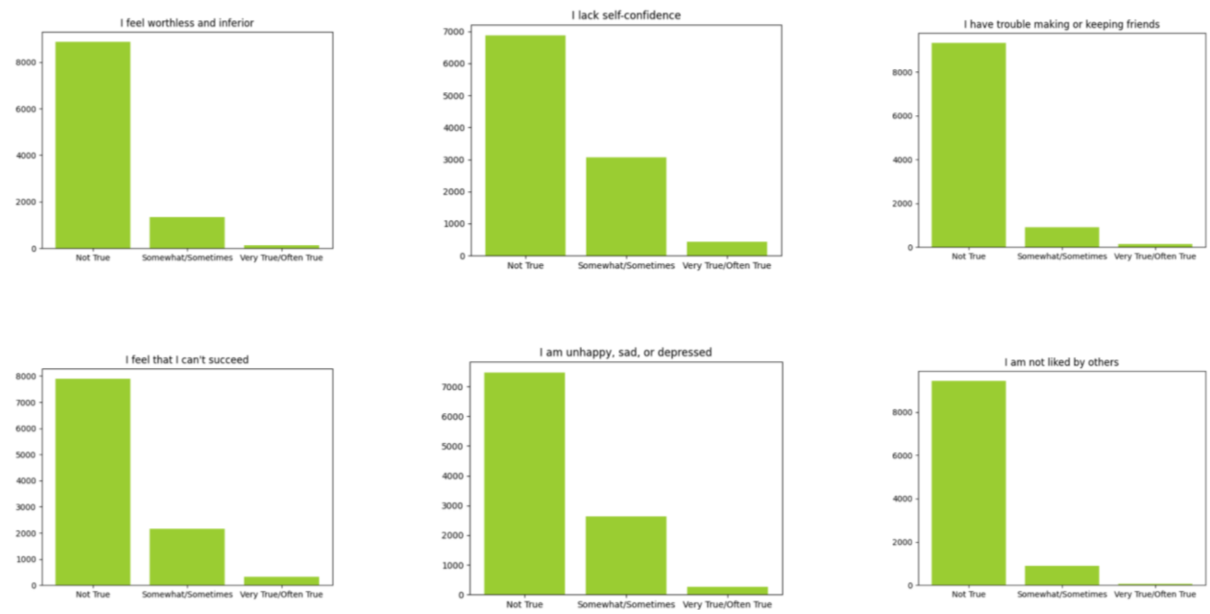



Figure 3. Internalizing symptom responses for the entire cohort (n=10,414 after null responses are removed).

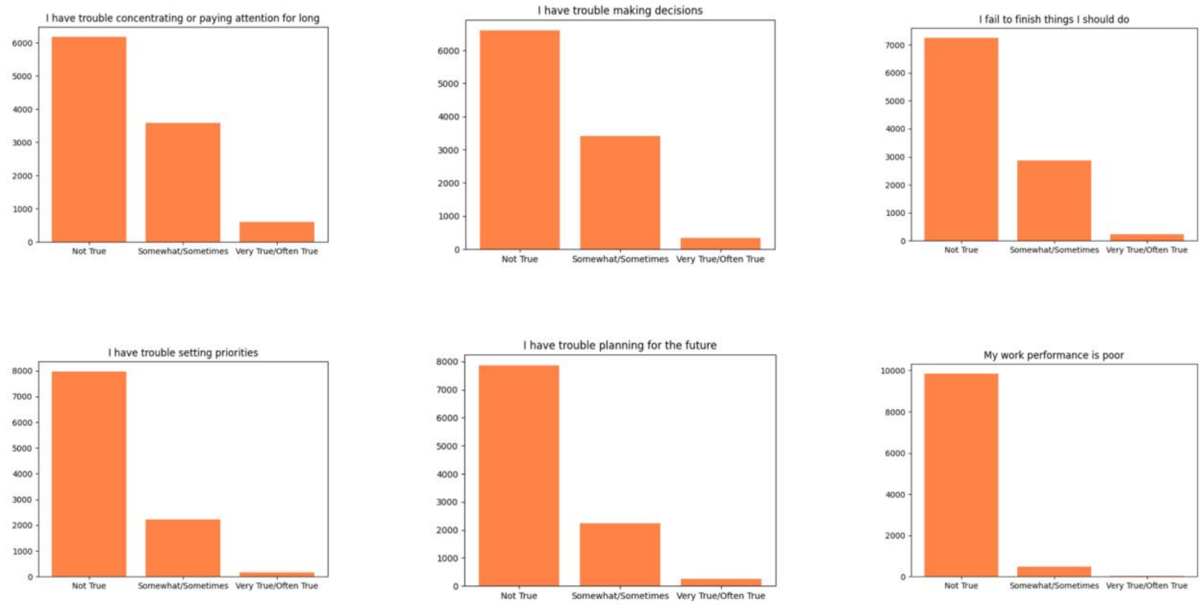



Figure 4. Attention symptom responses for the entire cohort (n=10,414 after null responses are removed).

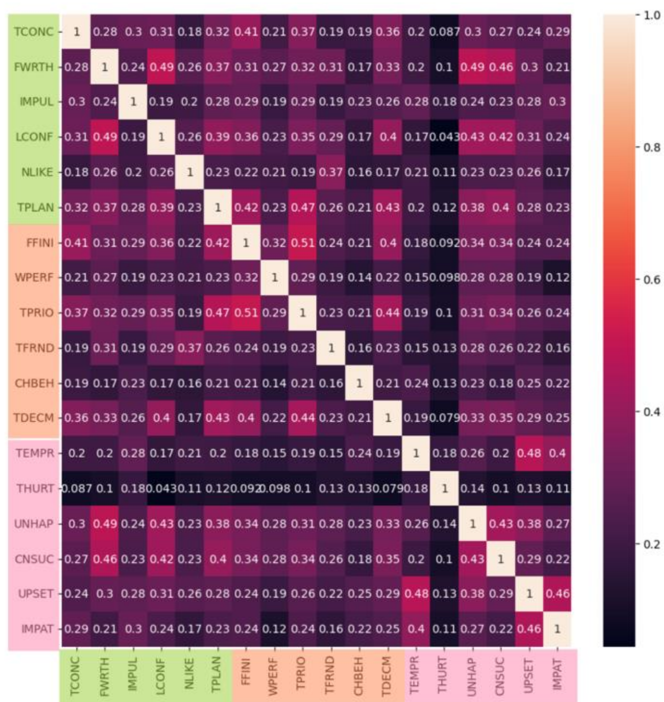



Figure 5. Correlations between parent psychological symptoms among the entire cohort (n=10,414 after null responses are removed). Symptoms are colored based on BPM item membership across three latent factors; sienna = attention, olive = internalizing, and violet = externalizing.

Based on the correlations we observe between specific symptoms in Figure 5, we hypothesize that utilizing psychological network models could show influence between specific symptoms and pinpoint which symptoms are most central to parent psychological network structure (Epskamp & Fried, 2018).

## Cohort Characteristics

Our low screen cohort consists of 2,360 children, 54.25% girls, 45.5% boys, and 0.25% transgender or don't know. The low screen cohort consists of an upper-middle class socioeconomic bracket where 1.6% of families reported annual family income <$5000; 1.9% reported $5000–$11,999; 1% reported $12,000–$15,999; 2.7% reported $16,000–$24,999; 3.4% reported $25,000–$34,999; 4.3% reported $35,000–$49,999; 9.9% reported $50,000–$74,999; 13.0% reported $75,000–$99,999; 37.5% reported $100,000–$199,999; 18.7% reported $200,000+; and 6.1% didn't know or refused to answer.

The low screen cohort identified as 83% White, 12.5% Hispanic, 8% Black, 5.3% Asian, and 2.2% other or prefer not to respond. The low screen cohort had a median age of 11.8 years old.

Our high screen cohort consists of 1,426 children, 39% girls, 59.6% boys, and 1.2% transgender or don't know. The high screen cohort consists of a middle-class socioeconomic bracket where 4% of families reported annual family income <$5000; 4% reported $5000–$11,999; 3.9% reported $12,000–$15,999; 5.2% reported $16,000–$24,999; 7.5% reported $25,000–$34,999; 10.7% reported $35,000–$49,999; 16.9% reported $50,000–$74,999; 12% reported $75,000–$99,999; 21% reported $100,000–$199,999; 3.8% reported $200,000+; and 9.7% didn't know or refused to answer.

The high screen cohort identified as 62% White, 20.4% Hispanic, 29% Black, 3% Asian, and 3.9% other or prefer not to respond. The high screen cohort had a median age of 12 years old.

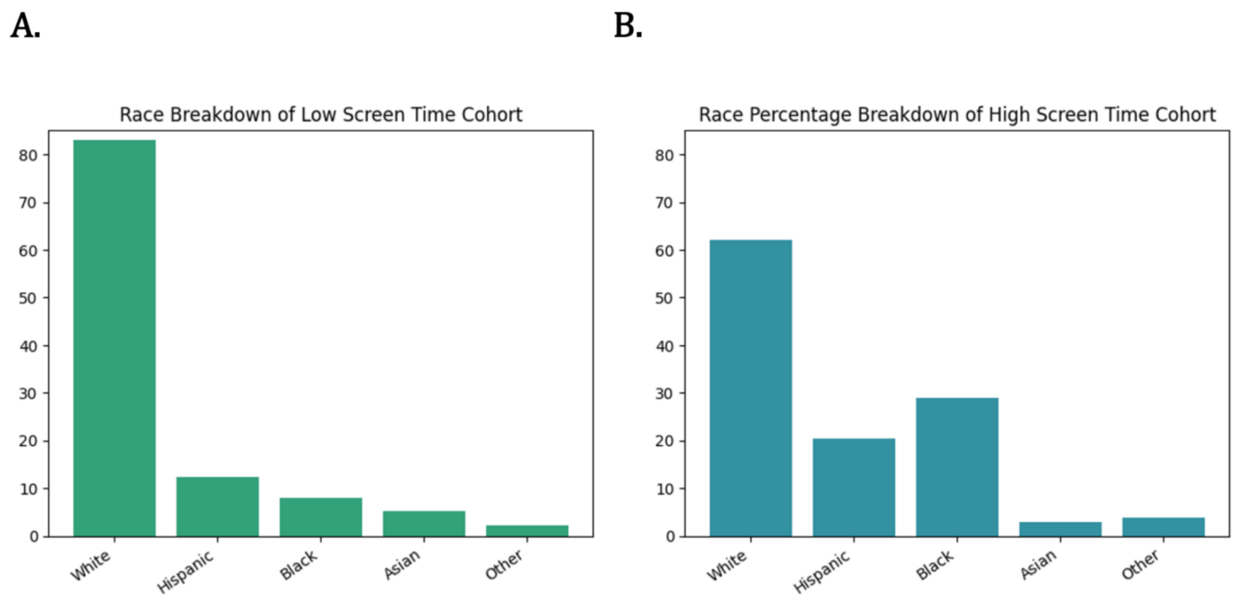



Figure 3. Percentage of child racial groups represented in the sample as identified by parents. (A) Low Daily Screen Use (<2 hours). (B) High Daily Screen Use (>6 hours).

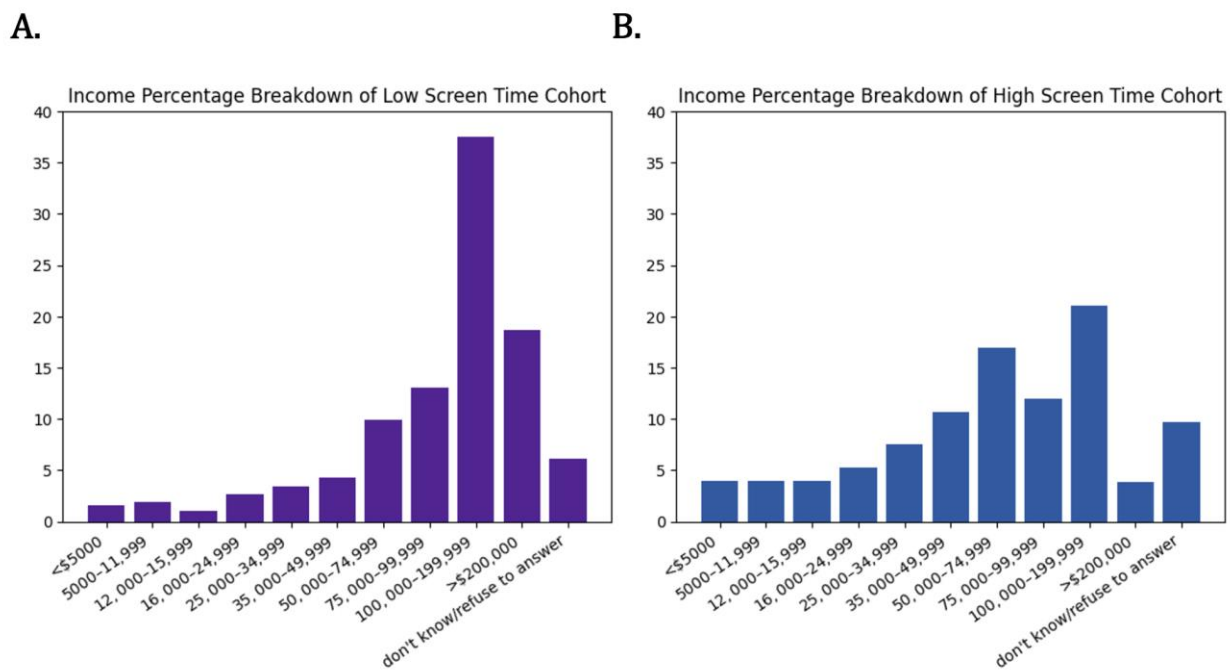



Figure 4. Percentage of income brackets represented in the sample as identified by parents. (A) Low Daily Screen Use (<2 hours). (B) High Daily Screen Use (>6 hours).

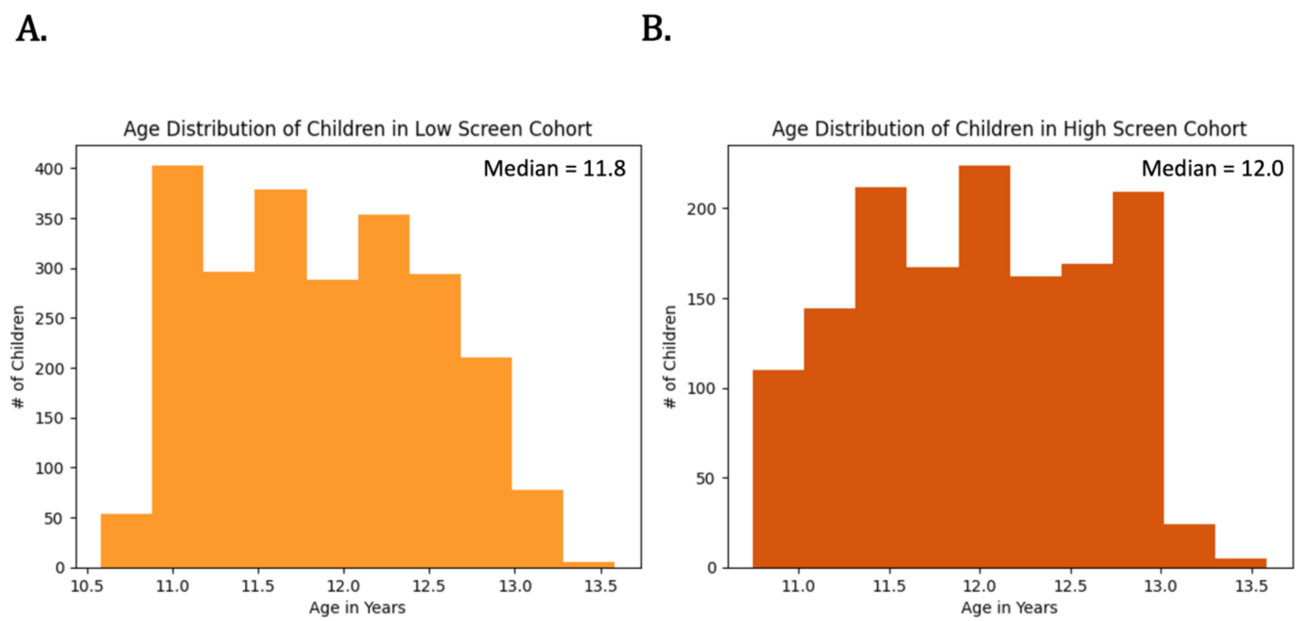



Figure 5. Age distributions of high and low screen time cohorts. (A) Low Daily Screen Use (<2 hours), median age = 11.8 years. (B) High Daily Screen Use (>6 hours), median age = 12.0 years.

## EBIC Polychoric Networks

In a novel approach to exploring the relationship between parent psychological problems and children's screen time, we explore a more nuanced analysis of parent mental health. We first randomly split our sample into 80% training and 20% testing and then using an EBIC mixed graphical model estimation network and the R mgm package, we compute a sparse Mixed Graphical Model (MGM) using lasso regularization. The tuning parameter for the lasso regularization is chosen utilizing the Extended Bayesian Information Criterion (EBIC) which is optimal for polychoric correlations as input data (Epskamp & Fried, 2018). Utilizing our training data, we choose the lasso hyperparameter, $\lambda$, by minimizing our EBIC scores for each individual node. We use the OR-rule which allows edges that are either significant in two directions or simply unidirectional and we specify that our data is categorical. Utilizing our testing data, we next check the accuracy of our model by checking the correct classifications of each node based on the nodes around it (Haslbeck & Waldorp, 2020). We also calculate the normalized accuracy and visualize this metric as a pie ring around each node. If a node has a negative normalized accuracy, we show a full yellow ring around the node. We then perform bootstrap resampling with nBoots = 100 to determine the reliability of each edge.

Once we have our estimated network, we examine the centrality of each node by estimating the stability of different centrality measures. We analyze the strength, expected influence, and betweenness of each symptom node. We plot our bootstrap stability for each edge within our network. This gives a general impression of the confidence of our network and allows us to visualize which edges are significant within the estimated network. We generated networks separately for high and low screen time cohorts.

To analyze our MGM network at a node level, we perform Mann-Whitney U Tests between high and low screen cohorts for each symptom node. Mann-Whitney tests compare the median values and the distributions around the median values of our two cohorts to compare whether the populations are different.

## EBIC Binary Networks

Next, we dichotomized our data to enable the use of a network comparison test between the high and low screen time networks. In the ABCD study, parents were asked to "For each item, select the response that describes YOURSELF (YOU, THE PARENT) over the past 6 months: I feel lonely: 0, Not True; 1, Somewhat/Sometimes; 2, Very True/Often True." To dichotomised the responses to the BPM questions we are using, we grouped "1, Somewhat/Sometimes" and "2, Very True/Often True." We use this dichotomized version of the parent responses to estimate our EBIC networks. We again use the OR-rule which allows edges that are either significant in two directions or simply unidirectional. We again specify our data to be categorical and set binarySign = TRUE.

Next, we perform the same centrality indices tests, case dropping tests, confidence interval visualizations, and normalized accuracy calculations we do for our EBIC polychoric network. Finally, using the binary data allows us to perform a network comparison test between our high and low cohort networks. We examine this network comparison test across each edge and overall to determine whether our networks are significantly different and which edges between the two cohorts differ.

## Results

Our estimated MGM produced with the EBIC polychoric model produces two different networks separated into parents in households with high child screen time versus low child screen time.

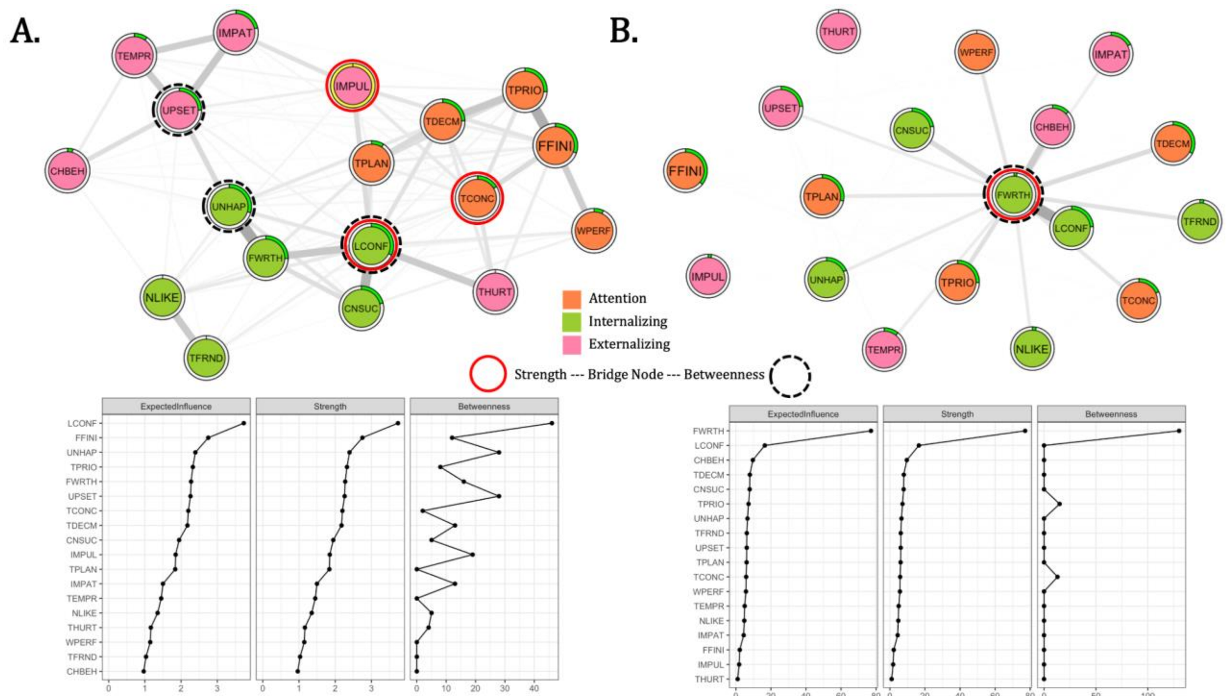



FIGURE 6. ESTIMATED POLYCHORIC MGM NETWORKS OF PARENTAL BPM SYMPTOMS SEPARATED BY CHILD SCREEN USE. Edges denote partial correlative associations with thicker lines representing stronger associations. Nodes are colored based on BPM item membership across three latent factors; sienna = attention, olive = internalizing, and violet = externalizing. Nodes at or above one standard deviation from the average in terms of bridge strength and bridge betweenness are outlined in solid red and dashed black lines, respectively. The model was generated on 80% of the data per cohort by minimizing EBIC scores to choose the optimal λ tuning parameters for the lasso regularization of each individual node. The green pie metrics encircling each node represent the normalized accuracy, or the proportion of correct classification normalized by the marginal distribution of the symptom, of the model in predicting that node and are generated using 20% of the data set aside for training. The yellow pie metric around IMPUL in panel A represents the negative normalized accuracy score for IMPUL within that network. Node centralities are ranked in descending order based on expected influence. (A) Low Daily Screen Use (<2 hours, n = 2,360). (B) High Daily Screen Use (>6 hours, n = 1,426).

We can compare the strength and expected influence of symptoms across the different cohorts but given the jumpiness of individual node betweenness, we do not think it is as reliable of a metric. We note that the top symptoms for the low screen time cohort differ from the high cohort. Within the high screen time network, we see FWRTH as a node with very high strength and expected influence. By looking at the high screen time network, we note that FWRTH is central to many other connected symptoms and stands out as the center of the network. However, we note that FWRTH has low normalized accuracy. No other nodes in the high screen time network show bridge strength or betweenness higher than one standard deviation above the average besides FWRTH. In the low network, LCONF, UNHAP, and UPSET stand out with high bridge betweenness while only LCONF shows high bridge strength between symptom communities. All four of these nodes have relatively higher normalized accuracy compared to the other symptoms in the network. On an individual node level, LCONF shows the highest expected influence and strength while FWRTH is the fifth strongest symptom (with less than 1/20 of the individual node strength when compared to FWRTH in the high screen time network). Finally, within the low network, we note that IMPUL has a negative normalized accuracy which is the case because the network model performs worse than the intercept/marginal model.

To examine node level changes, we calculated Mann-Whitney U-scores for each node across the two networks.

| Node | U-Statistic | P-Value |
|---|---|---|
| TCONC: "I have trouble concentrating or paying attention for long" | 1604991.0 | 0.005599 |
| TPLAN: "I have trouble planning for the future" | 1582876.5 | 2.8038e-0.5 |
| TFRND: "I have trouble making or keeping friends" | 1636918.0 | 0.005864 |
| CNSUC: "I feel that I can't succeed" | 1613469.0 | 0.003829 |
| IMPUL: "I am impulsive or act without thinking" | 1617043.5 | 0.00020155 |
| TEMPR: "I have a hot temper" | 1595818.0 | 0.0002348 |
| THURT: "I threaten to hurt people" | 1663834.5 | 2.5927e-05 |

Table 2. Significant Mann-Whitney tests across symptom nodes between high (>6 hours, n = 1,426) and low (<2 hours, n = 2,360) screen time networks.

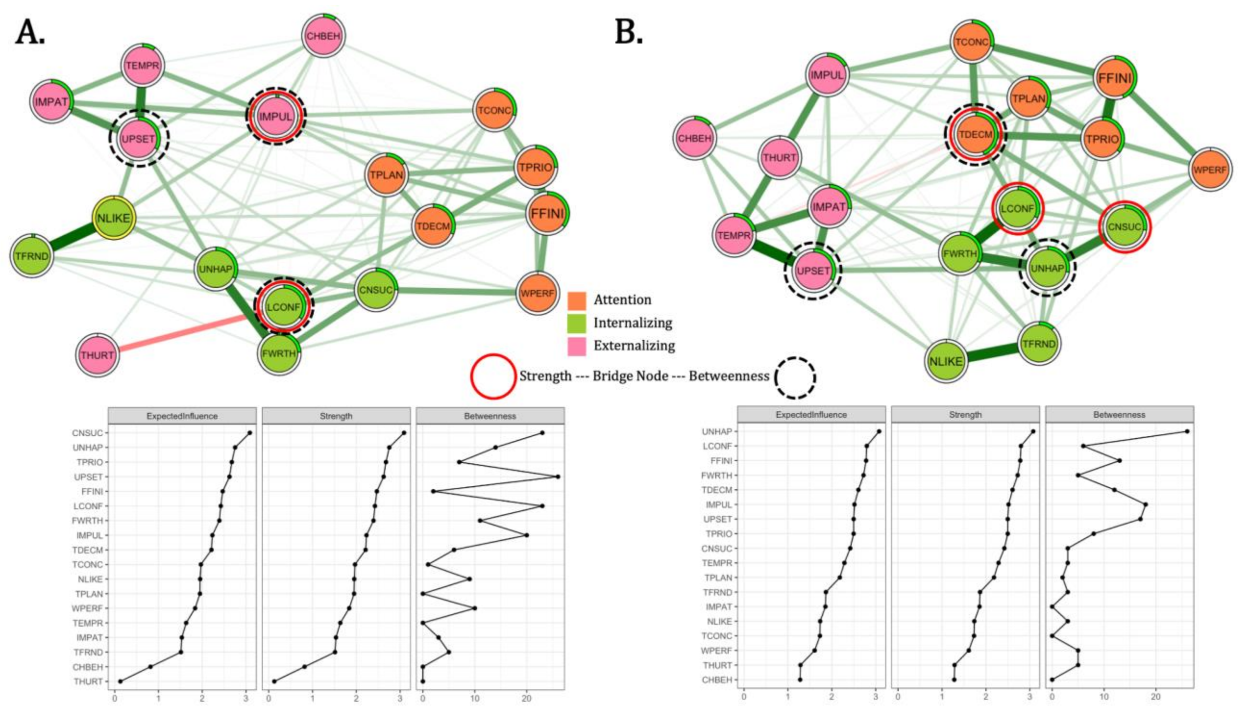



FIGURE 8. ESTIMATED BINARY MGM NETWORKS OF PARENTAL BPM SYMPTOMS SEPARATED BY CHILD SCREEN USE. Edges denote partial correlative associations with thicker lines representing stronger associations. Nodes are colored based on BPM item membership across three latent factors; sienna = attention, olive = internalizing, and violet = externalizing. Nodes at or above one standard deviation from the average in terms of bridge strength and bridge betweenness are outlined in solid red and dashed black lines, respectively. The model was generated on 80% of the data per cohort by minimizing EBIC scores to choose the optimal λ tuning parameters for the lasso regularization of each individual node. The green pie metrics encircling each node represent the normalized accuracy, or the proportion of correct classification normalized by the marginal distribution of the symptom, of the model in predicting that node and are generated using 20% of the data set aside for training. The yellow pie metric around NLIKE in panel A represents the negative normalized accuracy score for NLIKE within that network. Node centralities are ranked in descending order based on expected influence. Node centralities are ranked in descending order based on expected influence. (A) Low Daily Screen Use (<2 hours, n = 2,360). (B) High Daily Screen Use (>6 hours, n = 1,426).

After estimating different networks between the polychoric and binary data, we compare them using model accuracy (CC), or the number of correctly classified responses out of the total, as well as normalized model accuracy. Normalized model accuracy (nCC) can be calculated using the following equation:

$$nCC = \frac{(CC - norm\_constant)}{(1 - norm\_constant)}$$

norm_constant is the highest relative frequency of any of the categories across the data (0, 1, or 2 for the polychoric and 0 or 1 for the dichotimized data) (Haslbeck & Waldorp, 2020). Utilizing this metric, we were able to gauge how well the models performed given the distribution of parent responses to psychological symptoms. We plot model accuracy and normalized model accuracy for all models.

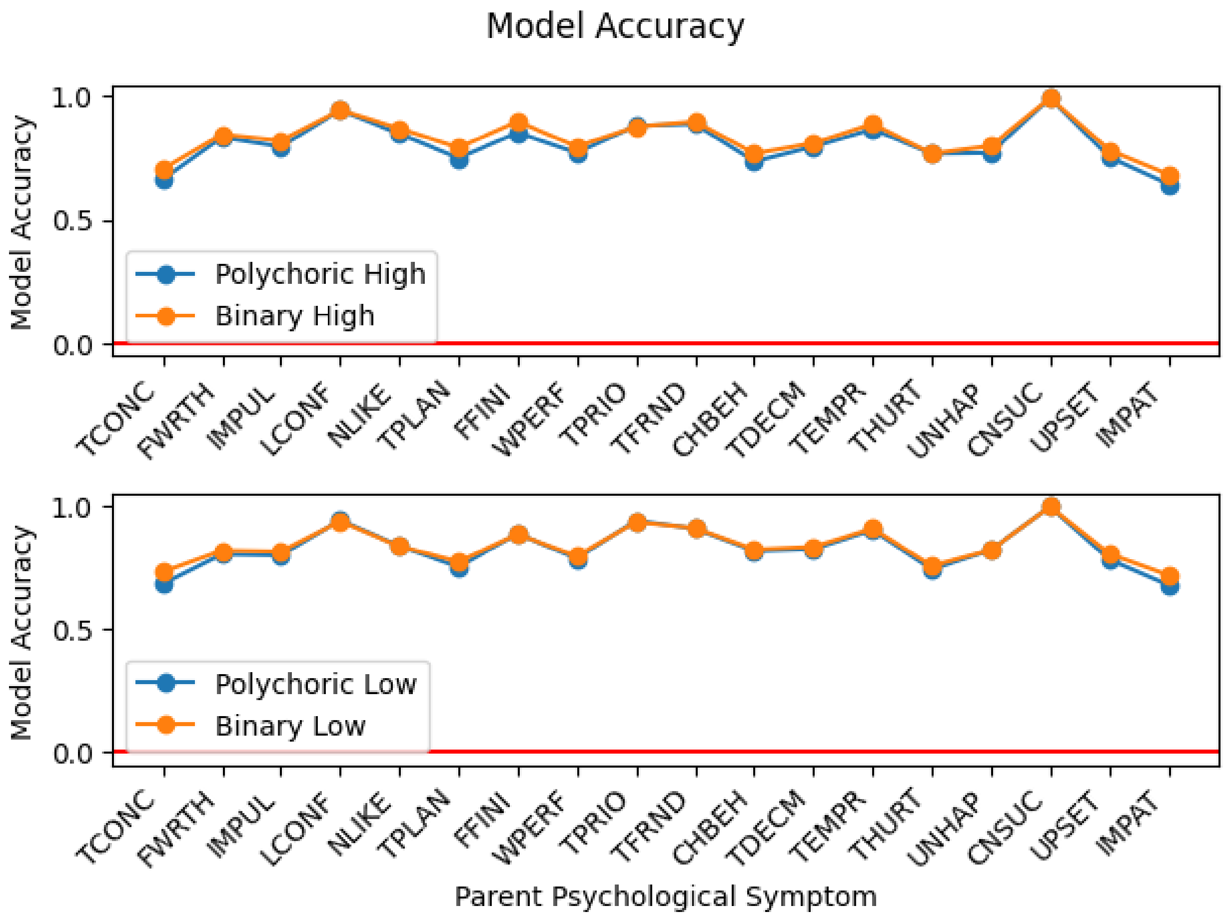



FIGURE 9. MODEL ACCURACY ACROSS DIFFERENT NETWORK ESTIMATIONS AND COHORTS. Model accuracy or correct classifications based on the testing set (20% of the total sample) are marked in their respective colors for high and low cohorts. The red line is drawn at y = 0.

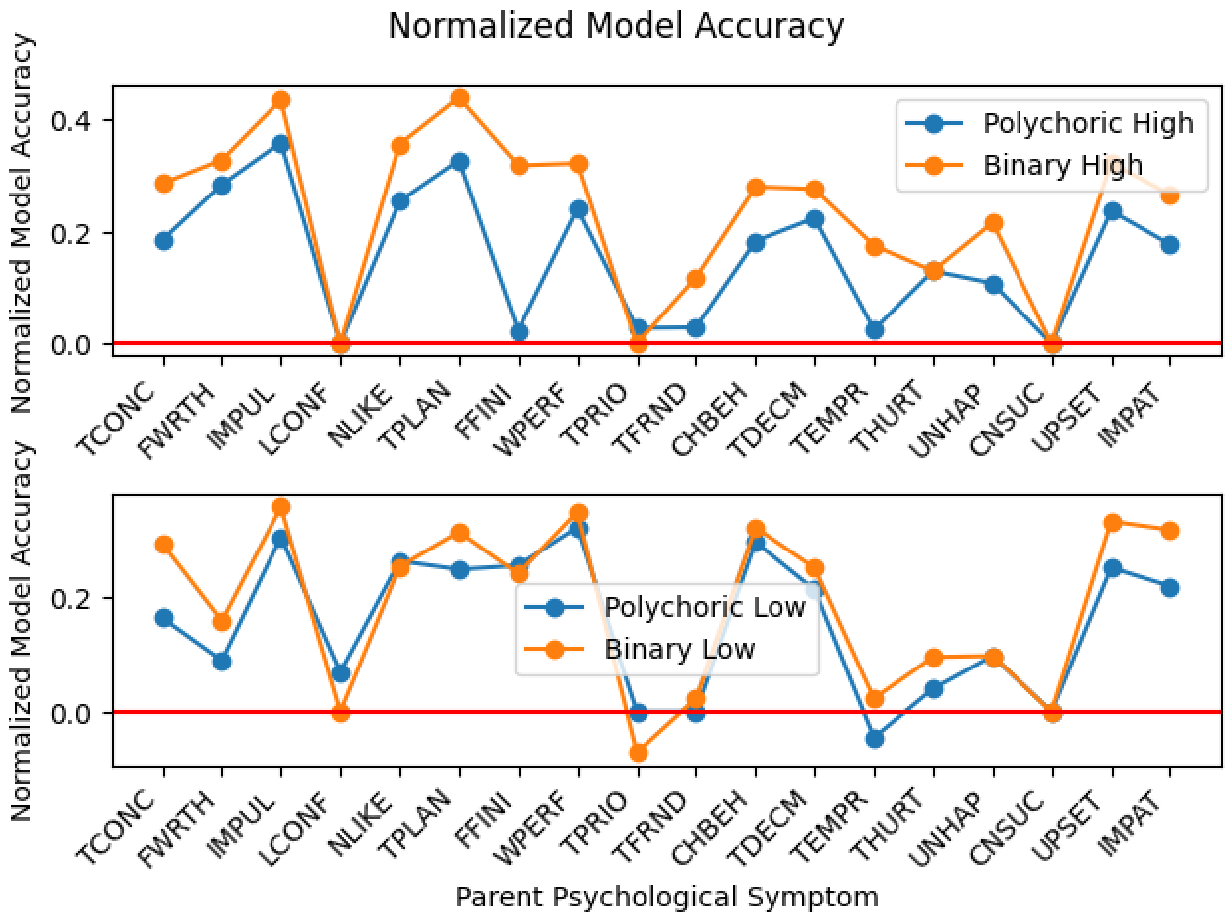



FIGURE 10. NORMALIZED MODEL ACCURACY ACROSS DIFFERENT NETWORK ESTIMATIONS AND COHORTS. Normalized model accuracy based on the testing set (20% of the total sample) is marked in their respective colors for high and low cohorts. Normalized model accuracy is the proportion of correct classification normalized by the marginal distribution of each individual symptom. Specifically, nCC = (CC - norm_constant)/(1 - norm_constant), where norm_constant is the highest relative frequency across the symptoms. The red line is drawn at $y = 0$ and negative accuracies indicate overfitting which occurs when the network model performs worse than the marginal model.

Since we ran one of our models on dichotomized data, we can now apply a network comparison test between the high and low screen time networks (van Borkulo et al., 2014). We run a network invariance test to find a test statistic of $M = 1.143737$ ($p = 0.841$). We next run a global strength invariance test to find a test statistic $S = 2.072847$ ($p = 0.608$). M represents the largest edge difference between the same two nodes across low and high child screen time networks while S is the general network strength or how activated a network is (Burger et al., 2020). Despite M not being significant, there are smaller differences between edges that are significant. We further explore specific edges that do vary between the low and high screen time networks.

| Node 1 | Node 2 | p-value |
|---|---|---|

| | | |
|---|---|---|
| TCONC: "I have trouble concentrating or paying attention for long" | CNSUC: "I feel that I can't succeed" | 0.013 |
| FWRTH: "I feel worthless and inferior" | CNSUC: "I feel that I can't succeed" | 0.049 |
| UNHAP: "I am unhappy, sad, or depressed" | CNSUC: "I feel that I can't succeed" | 0.049 |
| TRPIO: "I have trouble setting priorities" | IMPUL: "I am impulsive or act without thinking" | 0.027 |
| TCONC: "I have trouble concentrating or paying attention for long" | CHBEH: "My behavior is very changeable" | 0.017 |
| TEMPR: "I have a hot temper" | CHBEH: "My behavior is very changeable" | 0.002 |

Table 3. Edge variations from a network comparison test between low and high dichotomized networks. While the largest difference between the same edge in low and high screen time networks is not significant (network invariance statistic M = 1.143737 (p = 0.841)), we report smaller edge differences that are significant between the high and low screen time binary networks.

## Discussion

Node centrality is typically represented using three indices: strength, expected influence, and betweenness. In our results, symptoms are ranked in order of increasing expected influence. Strength represents how connected a node is to other nodes while expected influence is the sum of a node's connections, representing the relative importance of a node in a network (Robinaugh et al., 2016). Thus, within a network, nodes with high centrality have strong connections to many other nodes and can act as hubs that connect otherwise isolated nodes to one another. Particularly in psychological networks, past research has shown the interconnected nature of high centrality nodes might make them especially important to the underlying causes, diagnosis, and treatment of mental disorders. Highly central nodes often serve as critical to upholding the whole network and can thus be studied as essential to understanding the relationships within the network (Robinaugh et al., 2016).

In our EBIC polychoric networks, we find that certain nodes are more connected within the network and, therefore, significantly stronger than others. Across both high and low GGM networks, we find that attention and internalizing symptoms are stronger within the networks, with the exception of the symptom UPSET and exclusively within the high screen time network, CHBEH. While CHBEH has the third highest expected influence in the high screen time network, it has the least expected influence in the low screen time network.

Within the high screen time MGM network, we find internalizing and attention symptoms are ranked as stronger than externalizing ones. When examining bridge communities, we interpret bridge strength as an indicator of a node’s total connectivity with symptoms in other communities (Jones et al., 2021). Within the internalizing community of the high screen time MGM network, we find only FWRTH as a node with bridge strength and betweenness higher than one standard deviation above the rest of the node bridge strengths and betweenness. FWRTH serves as the center of the network visually and from the individual expected influence, clearly serves to influence many other parent psychosocial symptoms in households with high child screen time. However, in our Mann-Whitney U-Tests, we do not find that FWRTH shows significantly differing distributions across low and high child screen time households. FWRTH shows a correct classification, or accuracy, score of 0.850 meaning that 85% of predictions for FWRTH based on other nodes were correct. While FWRTH may have high accuracy, we normalize FWRTH's accuracy to calculate a value of 0.023. Compared to other symptoms in the network, FWRTH has very low normalized accuracy and thus, we believe that the lack of distribution of parent responses to "I feel worthless and inferior" is causing FWRTH to seem like the center of the parent psychological symptom network in households with high child screen usage.

Increased screen time is an example of child behavior that has been shown to be correlated with parental mental illness (Pulkki-Råback et al., 2022). While causal relationships have not been explored yet, analysis of specific parent mental illness symptoms and their centrality within networks could help pinpoint specific symptoms to target for analysis of how parent mental illness impacts children. We tentatively propose that FWRTH is a parent symptom that can be targeted for further exploration and possibly specialized treatment. Because of its very high bridge strength, bridge betweenness, individual strength, and individual expected influence, we suggest that removing FWRTH from the high screen time network would destabilize the network. Furthermore, we propose that investigating LCONF in high screen time households might also be useful. LCONF strongly influences FWRTH and has a much higher normalized accuracy, meaning that we can more reliably predict parent answers to "I lack self-confidence" based on other nodes in the network compared to FWRTH. We interpret this strong association between LCONF and FWRTH, LCONF's higher normalized accuracy, and FWRTH's centrality to mean that LCONF could be significantly influencing parent psychological networks in households where children have high average screen behavior.

In addition to focused consideration of FWRTH and LCONF in high screen time networks, we propose THURT, IMPUL, and FFINI as symptoms that have no significant strength or expected influence in the high screen time network. While THURT and IMPUL are significantly different in low and high screen time populations, they are not influential or even connected in the high screen time network, implying that change in these nodes does not change the rest of the network (Robinaugh et al., 2016). FFINI is not significantly different in terms of distribution between the low and high networks but shows influence in the low screen time network and not the high screen time network. THURT and IMPUL fall into the externalizing symptom group and thus, we suggest that externalizing symptoms (these two in particular) are less important for determining the overall network structure. We interpret the significant difference in these symptoms between low and high screen time groups to mean that these symptoms are more present in households where children have higher screen times but that these symptoms do not contribute to the overall relationships between parent symptoms. We note that THURT and IMPUL both have very skewed distributions of parent responses in both low and high polychoric networks and this observation may be responsible for the lack of relationships between these symptoms and others. This observation is further fortified by the very low normalized accuracy shown on these nodes.

In general, internalizing and attention nodes had higher strengths and expected influence within the high screen time polychoric network, suggesting these groups of categories were more influential in impacting other network symptoms and were most critical to network structure. We suggest that targeted treatment and decreases in internalizing and attention symptoms, specifically FWRTH and LCONF, could help reduce relationships across the high screen time polychoric network.

Within our binary networks, we can see that there are a lot more relationships between symptoms especially between externalizing symptoms and other symptom communities. Overall, it is harder to see a clear picture of what is going on based simply on looking at the data. We do see is high bridge betweenness in UPSET in both the low and high networks, exactly as we saw it in the EBIC polychoric low screen time network. We see LCONF and CNSUC as nodes with high bridge strength in both low and high networks. Because we are using binary data, we can perform a network invariance test as well as a global strength invariance test. While neither are significant, we argue that there are significant edges that differ between the low and high child screen time networks. Past research says that a network comparison test is not reliable if M is not significant but we argue that these edges are still worth looking at (van Borkulo et al., 2014). Just because the largest difference between two edges isn't significant doesn't mean that there aren't significantly different edges across the networks with slightly smaller differences. Furthermore, according to past studies, since the sample size is different for the two networks, the network invariance statistic might not be a perfect measure of significance (van Borkulo et al., 2022). When we did dive into the specific edges that were different across the high and low network, we found that 3 out of the 6 edges that were different involved CNSUC. This seems consistent with our analysis that CNSUC is a strong bridge node in both low and high child screen time networks.

From the individual strength of symptoms within our EBIC polychoric networks in internalizing and attention communities, we find that parent internalizing and attention symptoms are more influential to parent psychological disorders, especially in high child screen time households. From the stand-out high bridge strength of "I feel worthless and inferior," we find that this is a key symptom for overall psychological network stability in high screen time households and further recommend analysis of the relationship between FWRTH and LCONF within high screen time households. FWRTH does not have a significantly different distribution across low and high screen time networks, meaning parents report feeling similarly worthless and inferior in low and high screen time households, yet it is the most central symptom in high screen time household networks. Furthermore, we note that one edge connected to FWRTH significantly changes in binary networks between low and high screen time households.

When analyzing our binary networks, we find UPSET to be a strong bridge betweenness node for both the low and high screen time networks. In the high screen time binary network, we observe TDECM as a node with high bridge betweennees and high bridge strength. Furthermore, TDECM does not show up as a node with either of these attributes in the low screen time network. The normalized accuracies for TDECM are higher in our binary networks than in our polychoric networks and are relatively high compared to other symptoms.

Utilizing normalized accuracy as a measure of model reliability, we interpret our EBIC binary networks to be better predictors of parent psychological symptoms in both low and high screen time households. With the exception of TPRIO and LCONF in both low and high screen time networks, all symptoms show higher normalized accuracies when dichotomized. This makes sense because we calculate normalized accuracy by dividing the correctly classified responses by (1 - norm_constant) where the norm_constant is the highest relative frequency of any of the categories. Thus, with only two categories, norm_constant is larger and (1 - norm_constant) is smaller, raising normalized accuracies. We interpret this observation to mean that both polychoric and binary networks have possibilities for interesting findings that warrant further research. Specifically, we suggest that the relationship between parent responses to FWRTH and LCONF be explored in high child screen time households as well as TDECM.

## Strengths and Limitations

Our use of ABCD data gives a nationally representative sample collected across racial and income groups. While past research exists on the relationships between parent mental illness and child screen time, we are not aware of previous studies that take an item-level approach to adult self-reported parent mental illness symptoms. Our item level approach to psychological symptoms gives us the strength of considering different symptoms within the same symptom categories rather than using one sum score that smooths over differences in symptom responses (Pulkki-Råback et al., 2022). We were able to remove data collected during the pandemic to eliminate the change that virtual school and isolation had on child screen time. Common-rater variance is a typical problem for surveys that ask parents to assess their behaviors and that of their children. In this study, we rule out common-rate variance because the ABCD study asked parents to rate their own psychological symptoms and children to rate their own screen usage.

One significant limitation of our study is the cross-sectional nature of our design. Because of the lack of longitudinal ASR data throughout the study, we cannot identify causality between parent symptoms and child screen behaviors. If future follow-ups to the ABCD Study include ASR responses, there may be ways to study causal relationships between parent psychological symptoms and child screen behaviors. There are also limitations in the reliability of children's self-reported screen measurements. Children may not be equally reliable across differing ages at estimating time and tracking their own screen times. They may also be inclined to report lower times because of societal views on screen usage.

Another limitation of our study is the data itself. As evidenced in Figures 2, 3, and 4, distributions of parent responses vary greatly between symptoms. Some symptoms like THURT have very few "sometimes/somewhat" and "very often/very true" responses and thus we were less able to build relationships between THURT and other symptoms. This could absolutely mean that this symptom is less worth exploring because few people answer positively to it but it could also mean that we didn't have enough data to build relationships with. THURT is one example of multiple symptoms that all experience a lack of positive parent responses.

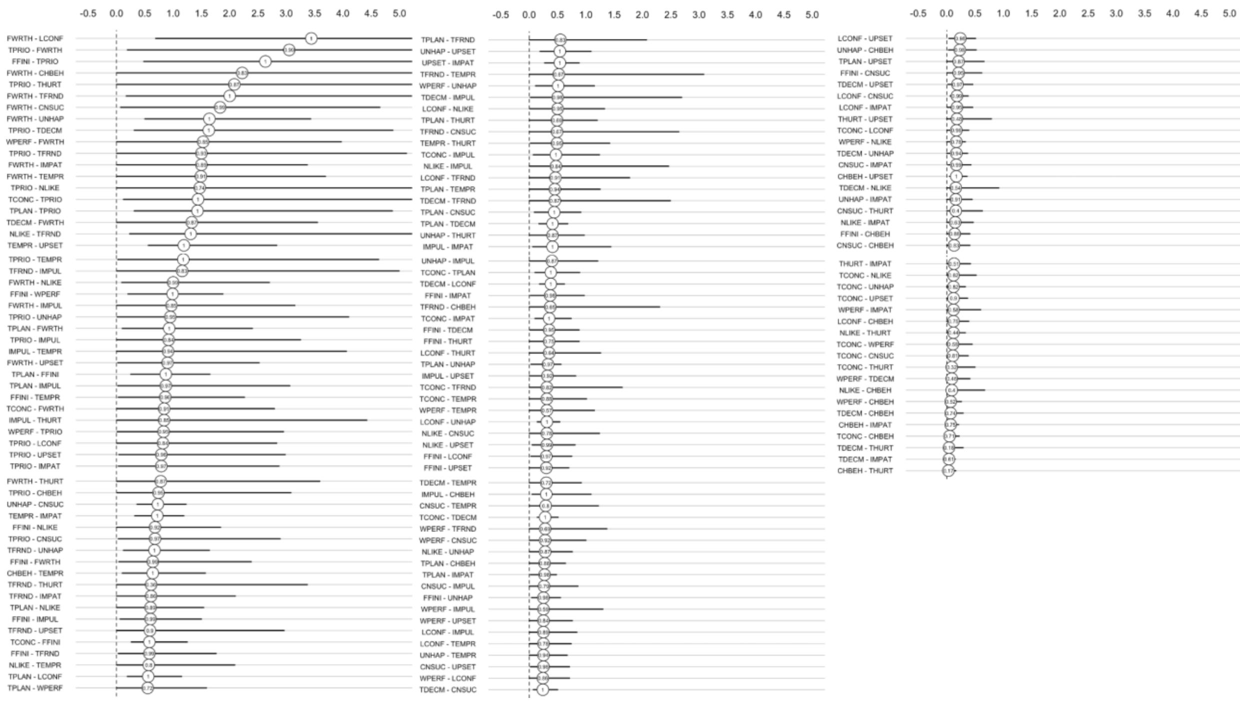
## Further Work

Given the timeframe for this project, we would have loved to explore a few methods further than stated here. Specifically, we would have loved to run bootstrap stability tests with nBoots = 1000 rather than nBoots = 100. We also would like to find a similar metric to the Correlation Stability Coefficient that serves to test reliability for Gaussian Graphical Models for our Mixed Graphical Models. We don't know of a numerical cutoff for our bootstrap stabilities that might enable us to declare certain centrality indices usable or nonusable. Finally, we suggest that future studies explore more symptoms than those shown in the BPM, looking specifically for symptoms with fewer "Not True" responses so that models might be built on more data. Specifically for the symptom THURT, there were very few nonzero answers in either high or low cohorts.

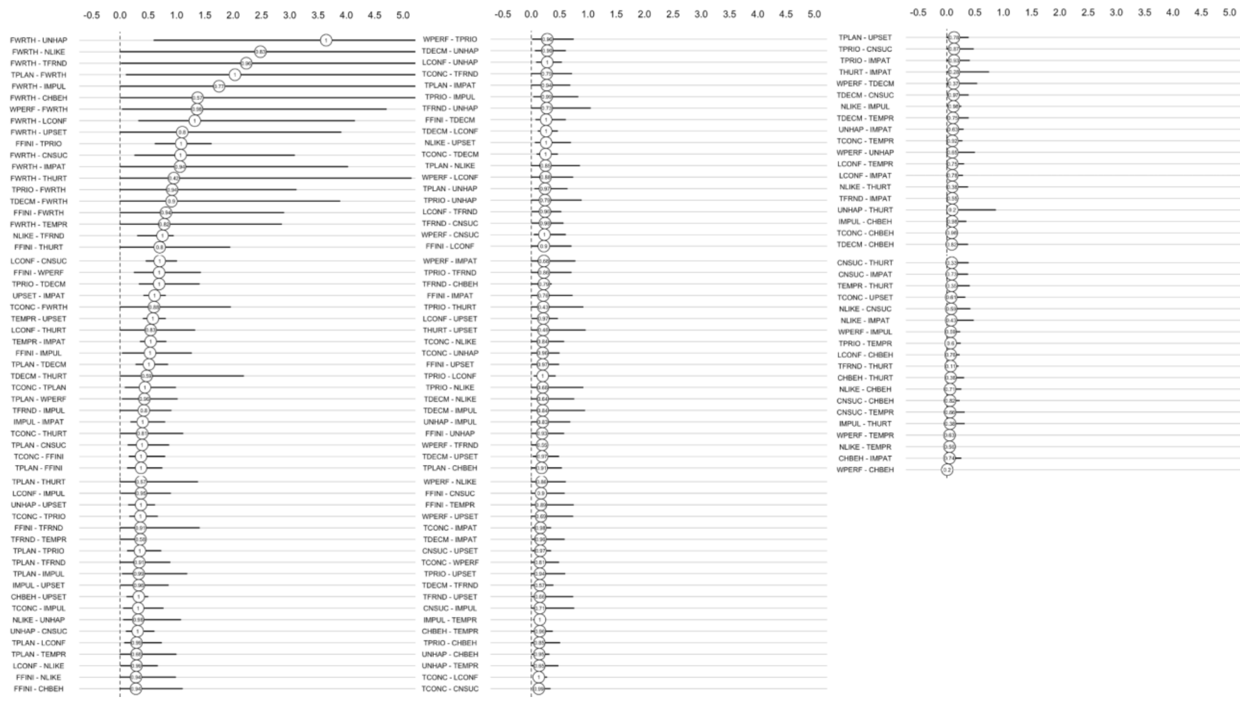
## Conclusion

In conclusion, this study uses child screen time as an example of a child behavior that has been shown to be impacted by parent mental illness. We propose that treatment of specific parent mental illness symptoms could destabilize connections between node symptom groups in our networks and perhaps be an avenue to changing how parent mental illness impacts child behavior. We find that our networks may not be very reliable across high and low screen time cohorts due to imbalances in parent responses to psychological self-report questionnaires. However, we do suggest that our work warrants further exploration of the relationships between parent responses to “I feel worthless and inferior” and “I lack self-confidence” in households where children show high screen time usage. Finally, we propose “I have trouble making decisions” as a symptom that holds together parent psychological binary networks in high child screen time households.

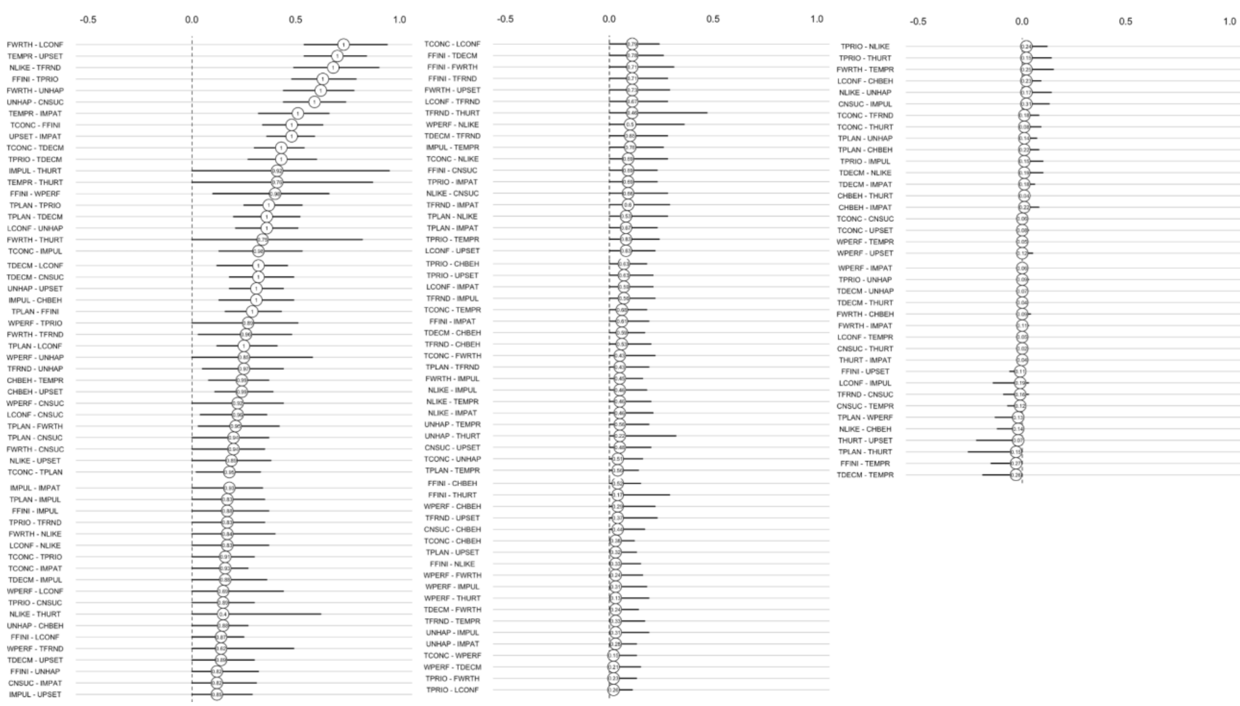
## Supplemental Figures



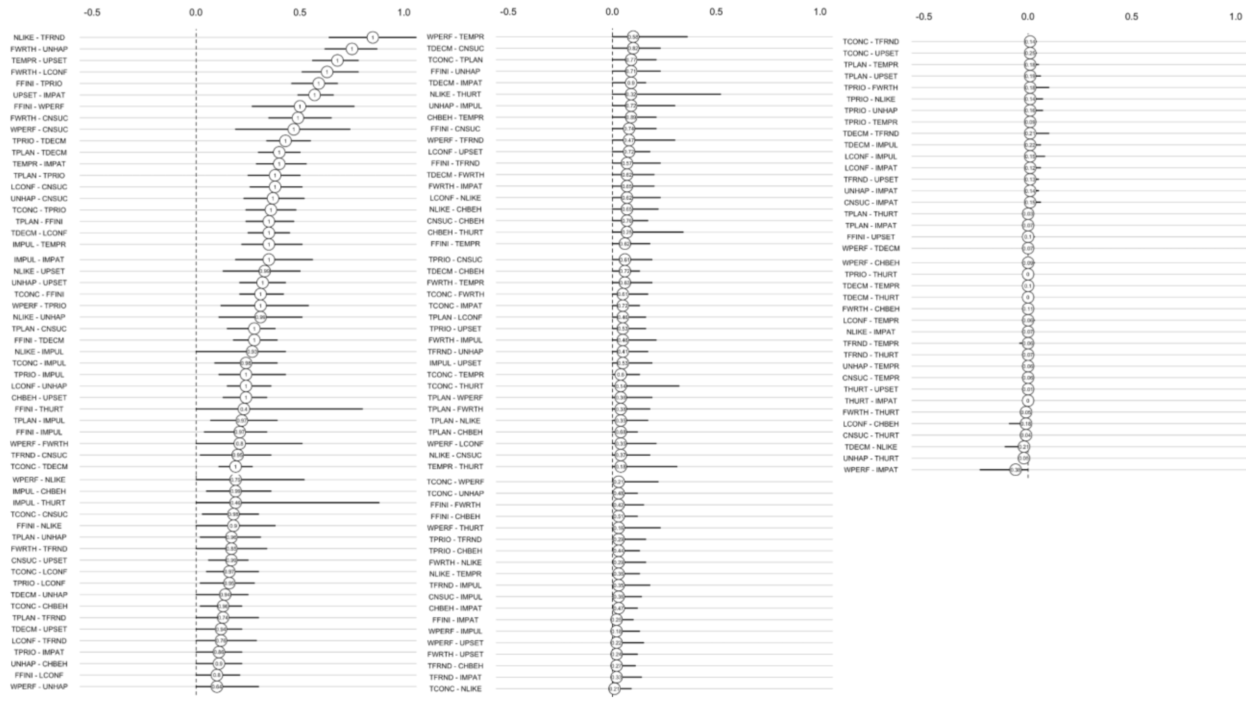
SUPPLEMENTAL FIGURE 1. Bootstrap stability for EBIC polychoric high screen time household network. The plot shows the proportion of re-samples which contain a non-zero link between two edges. For example, TPRIO - FWRTH shows in 99 of 100 bootstraps, there is a non-zero link between these two symptoms. nBoots = 100.



SUPPLEMENTAL FIGURE 2. Bootstrap stability for EBIC polychoric low screen time household network. The plot shows the proportion of re-samples which contain a non-zero link between two edges. For example, FWRTH - NLIKE shows in 83 of 100 bootstraps, there is a non-zero link between these two symptoms. nBoots = 100.



SUPPLEMENTAL FIGURE 3. Bootstrap stability for EBIC binary high screen time household network. The plot shows the proportion of re-samples which contain a non-zero link between two edges. For example, IMPUL - THURT shows in 92 of 100 bootstraps, there is a non-zero link between these two symptoms. nBoots = 100.



SUPPLEMENTAL FIGURE 4. Bootstrap stability for EBIC binary low screen time household network. The plot shows the proportion of re-samples which contain a non-zero link between two edges. For example, NLIKE - UPSET shows in 99 of 100 bootstraps, there is a non-zero link between these two symptoms. nBoots = 100.

| Node | Polychoric High | Polychoric Low | Binary High | Binary Low |
|---|---|---|---|---|
| TCONC: "I have trouble concentrating or paying attention for long" | 0.661 | 0.684 | 0.703 | 0.733 |
| TPLAN: "I have trouble planning for the future" | 0.832 | 0.805 | 0.843 | 0.82 |
| FFINI: "I fail to finish things I should do" | 0.794 | 0.801 | 0.818 | 0.816 |
| WPERF: “My work performance is poor", | 0.941 | 0.943 | 0.941 | 0.939 |
| TRPIO: "I have trouble setting priorities" | 0.846 | 0.839 | 0.867 | 0.837 |
| TDECM: "I have trouble making decisions" | 0.748 | 0.754 | 0.79 | 0.775 |
| FWRTH: "I feel worthless and inferior" | 0.85 | 0.888 | 0.895 | 0.886 |
| LCONF: "I lack self-confidence" | 0.769 | 0.788 | 0.794 | 0.797 |

| | | | | |
|---|---|---|---|---|
| NLIKE: "I am not liked by others" | 0.878 | 0.941 | 0.874 | 0.936 |
| TFRND: "I have trouble making or keeping friends" | 0.885 | 0.909 | 0.895 | 0.911 |
| UNHAP: "I am unhappy, sad, or depressed" | 0.734 | 0.818 | 0.766 | 0.824 |
| CNSUC: "I feel that I can't succeed" | 0.794 | 0.826 | 0.808 | 0.835 |
| IMPUL: "I am impulsive or act without thinking" | 0.864 | 0.903 | 0.885 | 0.909 |
| CHBEH: "My behavior is very changeable" | 0.766 | 0.744 | 0.766 | 0.758 |
| TEMPR: "I have a hot temper" | 0.769 | 0.822 | 0.797 | 0.822 |
| THURT: "I threaten to hurt people" | 0.99 | 0.998 | 0.99 | 0.998 |
| UPSET: "I get upset too easily" | 0.752 | 0.784 | 0.78 | 0.807 |
| IMPAT: "I am too impatient" | 0.643 | 0.68 | 0.682 | 0.72 |

SUPPLEMENTAL TABLE 1. Model accuracy or correct classifications based on the testing set (20% of the total sample). See Figure 9 for a graphical representation.

| Node | Polychoric High | Polychoric Low | Binary High | Binary Low |
|---|---|---|---|---|
| TCONC: "I have trouble concentrating or paying attention for long" | 0.185 | 0.163 | 0.286 | 0.292 |
| TPLAN: "I have trouble planning for the future" | 0.284 | 0.089 | 0.328 | 0.158 |
| FFINI: "I fail to finish things I should do" | 0.359 | 0.304 | 0.435 | 0.356 |
| WPERF: “My work performance is poor", | 0 | 0.069 | 0 | 0 |
| TRPIO: "I have trouble setting priorities" | 0.254 | 0.262 | 0.356 | 0.252 |
| TDECM: "I have trouble making decisions" | 0.327 | 0.247 | 0.439 | 0.312 |

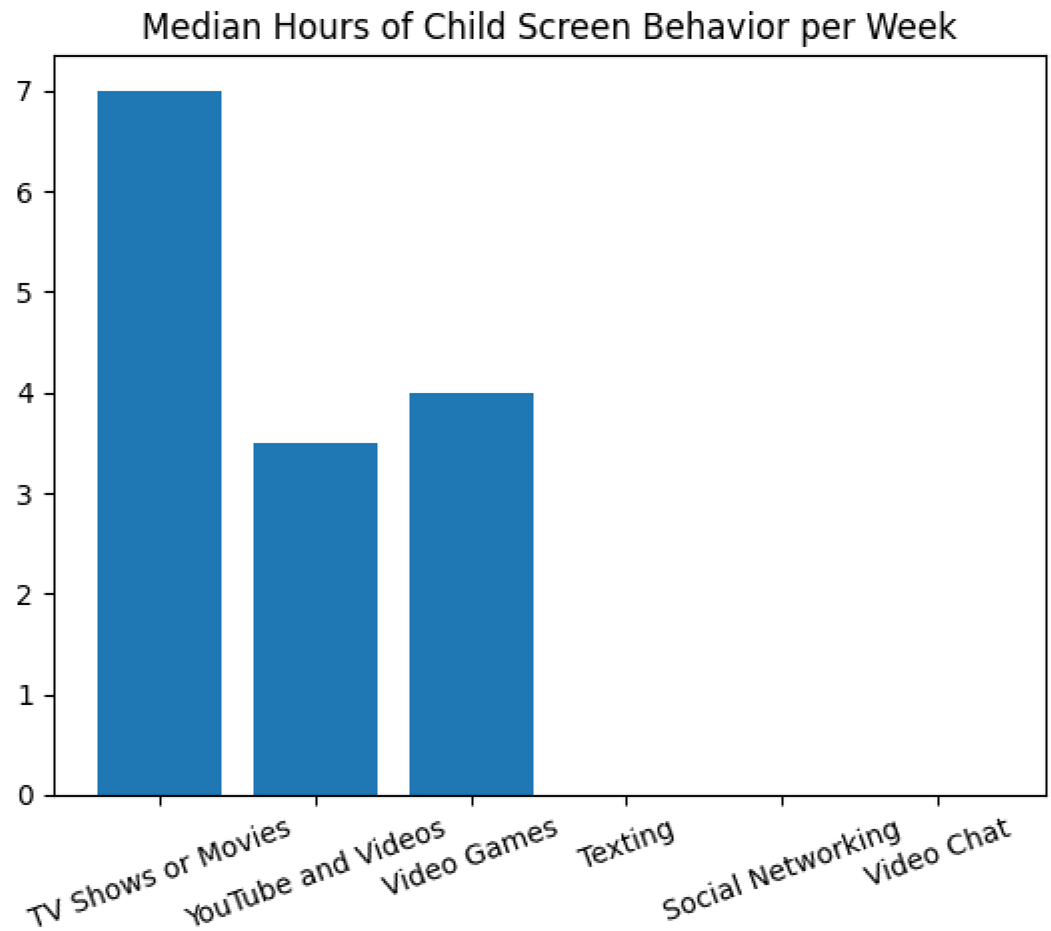
| | | | | |
|---|---|---|---|---|
| FWRTH: "I feel worthless and inferior" | 0.023 | 0.254 | 0.318 | 0.239 |
| LCONF: "I lack self-confidence" | 0.241 | 0.32 | 0.322 | 0.347 |
| NLIKE: "I am not liked by others" | 0.028 | 0 | 0 | -0.071 |
| TFRND: "I have trouble making or keeping friends" | 0.029 | 0 | 0.118 | 0.023 |
| UNHAP: "I am unhappy, sad, or depressed" | 0.183 | 0.295 | 0.28 | 0.32 |
| CNSUC: "I feel that I can't succeed" | 0.224 | 0.212 | 0.276 | 0.25 |
| IMPUL: "I am impulsive or act without thinking" | 0.025 | -0.045 | 0.175 | 0.023 |
| CHBEH: "My behavior is very changeable" | 0.13 | 0.04 | 0.13 | 0.095 |
| TEMPR: "I have a hot temper" | 0.108 | 0.097 | 0.216 | 0.097 |
| THURT: "I threaten to hurt people" | 0 | 0 | 0 | 0 |
| UPSET: "I get upset too easily" | 0.237 | 0.25 | 0.323 | 0.331 |
| IMPAT: "I am too impatient" | 0.177 | 0.218 | 0.266 | 0.316 |

SUPPLEMENTAL TABLE 2. Normalized model accuracy based on the testing set (20% of the total sample). See Figure 10 for a graphical representation.

| Node | U-Statistic | P-Value |
|---|---|---|
| TCONC: "I have trouble concentrating or paying attention for long" | 1604991.0 | 0.005599 |
| TPLAN: "I have trouble planning for the future" | 1582876.5 | 2.8038e-0.5 |
| FFINI: "I fail to finish things I should do" | 1650031.0 | 0.20265 |

| | | |
|---|---|---|
| WPERF: “My work performance is poor", | 1665800.5 | 0.16108 |
| TRPIO: "I have trouble setting priorities" | 1666198.0 | 0.4889 |
| TDECM: "I have trouble making decisions" | 1667530.0 | 0.5788 |
| FWRTH: "I feel worthless and inferior" | 1647591.0 | 0.08335 |
| LCONF: "I lack self-confidence" | 1677752.0 | 0.85345 |
| NLIKE: "I am not liked by others" | 1615741.5 | 2.9107 |
| TFRND: "I have trouble making or keeping friends" | 1636918.0 | 0.005864 |
| UNHAP: "I am unhappy, sad, or depressed" | 1557202.5 | 6.4521 |
| CNSUC: "I feel that I can't succeed" | 1613469.0 | 0.003829 |
| IMPUL: "I am impulsive or act without thinking" | 1617043.5 | 0.00020155 |
| CHBEH: "My behavior is very changeable" | 1640715.5 | 0.10077 |
| TEMPR: "I have a hot temper" | 1595818.0 | 0.0002348 |
| THURT: "I threaten to hurt people" | 1663834.5 | 2.5927e-05 |
| UPSET: "I get upset too easily" | 1650108.0 | 0.2153 |
| IMPAT: "I am too impatient" | 1669600.0 | 0.64311 |

SUPPLEMENTAL TABLE 3. All Mann-Whitney U-Tests between polychoric high and low cohorts.




SUPPLEMENTAL FIGURE 5. Median screen times per week across six behaviors: TV shows or movies, YouTube and Videos, Video Games, Texting, Social Networking, and Video Chat.

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