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Pixels and perception: Mapping the association between digital media and psychotic-like experiences in adolescents

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ABSTRACT

Introduction: Psychotic-like experiences (PLEs) during adolescence can lead to psychotic disorders. Digital media usage has been suggested to link to PLEs, but research is limited on how different types of screen exposure may differentially relate to PLEs over time. This study aimed to examine longitudinal associations between screen usage patterns and PLEs in adolescents.
Methods: Participants comprised 11,876 adolescents assessed annually from ages 9–12 years as part of the Adolescent Brain Cognitive Development study (ABCD). Screen usage (TV, video games, online video, social media, texting, video chat) and PLEs were assessed via self-report. Longitudinal network analysis models were estimated to examine connections between screen usage types and PLEs across three time points.
Results: Two clusters were formed, including *digital media for socializing* (e.g., social media/texting/video chat) and *digital media for entertainment* (e.g., online video/video games/TV). Texting and online video(s) had the highest centrality at each time point, suggesting importance in the network. PLE symptoms of hallucinations and concentration difficulties exhibited higher centrality than other symptoms. Online video and TV were influential bridges between screen usage and PLEs. Network structure significantly differed between ages 9–10 and 10–12 years, but global strength was unchanged over time.
Discussion: Results highlight the importance of understanding the associations between specific screen usage types and PLE symptoms. Texting and online video usage appear most influential in the development of adolescent PLEs over time. Findings can inform targeted interventions to promote healthy screen habits and reduce PLEs in at-risk youth.

1. Introduction

Psychosis is defined as the presence of hallucinations (i.e., sensory misperceptions) and/or delusions, resulting in an impaired ability to differentiate between what is reality and what is not (i.e., intense ideas underpinning biased interpretations of reality [1]). Psychosis is the defining feature of schizophrenic disorders, plays often a role in several mood and substance use disorders, and is also commonly seen in different types of neurological and medical conditions [1,2]. The impact of psychotic disorders can be quite severe, decreasing one's quality of life and increasing the risk of a variety of health issues (i.e., cognitive issues, impaired emotional regulation, impaired social functioning, sexual dysfunction, suicidal thoughts; problematic concurrent and prospective adaptation [3–7]. Nonetheless, psychotic symptoms (i.e., delusions, hallucinations, disorganised speech, etc.) have been supported to vary on a continuum of severity, with psychotic experiences extending from individuals within clinical populations (i.e. diagnosed) to less severe presentations (i.e. an individual's life may not be significantly impacted/compromised) in the general population [8]. Thus, research investigating the variability, as well as the associations of psychotic symptoms with everyday life behaviours, in non-clinical samples or broader community cohorts is imperative (i.e., Psychotic-Like Experiences [PLEs; 9]).

Before developing a psychotic disorder, prospective sufferers usually enter a prodromal phase experiencing significant mood changes and PLEs [10]. PLEs are defined as subclinical presentations of psychotic symptoms (e.g., hearing one's name being called in a crowd and/or unreasonably assuming negative intentions of others [11]). Interestingly, PLEs present to also follow a specific developmental trajectory, being most prevalent during ages 9–12 (17%) and decreasinging

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between 13 and 17 years old, likely as a side effect of maturation and gradual reduction in the influence of one's fantasy (7.5% [11]). While PLEs tend to decrease during adolescence, a small subset of individuals appears to deviate (i.e. not weakening or even experiencing enhanced PLEs) and go on to develop psychotic-spectrum disorders (e.g., Schizophrenia, Schizoaffective disorder [2]).

In light of such literature, PLEs have been considered by a portion of scholars in psychological research as an extension of the psychosis spectrum [9,11]. One of the underlying concepts supporting the validity of studying PLEs as part of the psychosis spectrum is the dimensionality/continuum hypothesis. This hypothesis suggests that a psychosis spectrum exists, with individuals likely changing place upon that continuum over time, depending on the interplay between their unique characteristics/predispositions and surrounding experiences [12,13]. Considering the possibility that PLEs represent subclinical manifestations of psychotic symptoms in the general population, research demonstrated that PLEs are relatively common in the wider community and are not limited to individuals experiencing psychotic symptoms [9]. Indeed, several studies have demonstrated a significant overlap between prodromal PLEs and later established psychotic disorders such as schizophrenia, supporting the validity of using/conceptualizing PLEs as an extension of the psychosis spectrum, and a risk indication of more severe, future presentations [14,15]. Moreover, neuroimaging studies have shown similar patterns of brain activity in individuals experiencing PLEs and those diagnosed with psychotic disorders [16]. Thus, using PLEs in psychological research as an extension, and likely a precursor, of psychotic disorders seems pertinent.

Traditionally, genetics were thought to be psychotic-spectrum disorders' predominant predisposing risk factor, yet researchers recently identified digital media use as a critical element, and likely a precipitating and/or perpetuating factor of PLEs (e.g. an individual's persecutory delusions may be triggered and/or reinforced by TV and/or web content [14,15]). Thus, considering that PLEs onset and digital media use may often associate, while being both more prevalent in youth years, it is essential to understand better, whether and how such associations may identify individuals at risk of psychosis early on [14,17]. To address these considerations, the present study aspires to contribute to the extant literature by investigating the influence of different screen usage exposure on PLEs.

2. Digital Media

An individual's development is co-shaped by different factors than 10 to 20 years ago due to the digital era [18]. For example, children aged 10–15 spend an average of 5.9 h daily on screens [19]. Indeed, digital usage is an important factor from a developmental perspective, as it has been associated with changes in neurobiology and mental health [20]. Interestingly, current literature demonstrates that digital use may positively and/or negatively affect wellbeing [21,22]. For example, adolescents with little to no digital use present to experience lower wellbeing than those who use it for 2–4 h daily. However, adolescents with very high levels of digital use (6+ hours) tend to report significantly lower levels of wellbeing [23,24]. Problematic digital media use (i.e., over-extended use and/or addiction) has also been shown to be detrimental to mental health [21,25]. For instance, it has been linked to an increased risk of symptoms related to somatisation, obsessive-compulsiveness, anxiety, and psychoticism among adults who spend more than three hours a day on the Internet [26]. These reinforce the hypothesis that problematic digital media use can be deleterious for mental health in a variety of domains, which can either result in and/or exacerbate pre-existing psychopathology [21].

Nevertheless, as there are different types of digital media facilitated via the Internet, popular digital platforms or TV, and for a variety of reasons such as entertainment, education, and socializing, their differential effects on mental health should be considered [18]. The Adolescent Brain Cognitive Development study (ABCD), which underpins the current project, categorizes the types of digital media as video games, social media, TV, online video chat, texting and online video (i.e., YouTube and Twitch). It has been supported that such different media types may operate differently regarding an individual's vulnerability to psychopathology [20]. Indeed, preliminary literature suggests that problematic internet use, such as disordered social media use and excessive gaming, may invite PLEs, as the person often disconnects from reality becoming immersed in the virtual world, which may in turn, for some users, influence the development of a psychotic disorder [14,15,27]. Addressing such concerns, Paquin and colleagues [28] investigated a sample of adolescents and young adults on the association between TV, social media and video game consumption on PLEs. They found significant positive relationships between all screen usage types on PLEs (TV and streaming: $r = 0.25$; social media use: $r = 0.28$; and video game use: $r = 0.23$ [28]). However, when the same relationships were assessed longitudinally, no significant links were revealed. Yet, they supported that a statistically small, longitudinal relationship does occur, and that their study may not have been sufficiently powered ($n = 425$) to evidence this association more clearly [28]. This calls for more research that has a sufficient sample size. So far, there appears to be no research that has specifically investigated online video, texting and video chat relationships with PLEs, while employing large cohort longitudinal data.

It is important to note that digital use is not always a risk factor for psychosis. When internet usage is moderate and used for mental health education purposes, psychotic-like experiences (PLEs) may decrease, and real-life social interactions, which may improve an individual's perception of reality, could be promoted [29]. Similarly, the frequency/intensity and the type of digital media consumed could likely change its potential effects on PLEs, being either positive or negative [28,29]. For example, Bonet and colleagues [30] found that 61% of individuals with a psychotic disorder felt their internet usage helped them socialize, while 23% and 20% of individuals felt frustrated and paranoid about their internet use, respectively. Overall, research has shown that digital media use can improve and/or exacerbate psychotic symptoms and PLEs based on time spent on digital media. Despite progress made, the available research to date often focused on relationships at the disorder level (i.e. psychosis as a whole entity), ignoring inter-item/symptom relationships (e.g. how delusions may distinctly associate with hallucinations compared to other psychotic symptoms), while also missing to emphasize how different types of screen exposure may affect one's development of PLEs. Thus, the present study will aim to contribute to the available knowledge, by concurrently examining the six different screen usage patterns available in the longitudinal, large cohort ABCD dataset, while also considering their associations with one's reported PLEs utilizing network analysis.

2.1. Network analysis

A psychopathology network comprises nodes representing different behaviours (i.e., PLE symptoms) connected through non-causal relationships or undirected edges [31]. Interestingly, network analysis visually represents an estimation of relationships between behaviours without assuming a specific latent construct, such as a psychotic disorder [32]. Indeed, unlike the dominant perspective in psychology, which emphasises interrelations at the construct level, network analysis evaluates the relationships between psychopathology symptoms, to in turn consider whether these inform an underpinning phenomenology network/cluster (e.g., different types of hallucinations and delusions [33]). The prevailing perspective suggests that mental disorders reflect a group of symptoms and can be explained by a latent construct (i.e., reflective approach), yet this may undermine the importance of specific symptomatology [34]. In contrast, network analysis conceptualises symptoms as mutually interacting with one another and informing the disorder (i.e., formative approach [35]). Similarly, it allows for the examination of comorbidity between symptoms within and across disorders and/or with other behaviours (i.e. screen usage patterns), including bridge symptoms, which can influence the transition between disorders and behaviours or their co-occurrence [36–38].

For that purpose, network analysis provides centrality indices to understand the importance of each symptom/behaviour/experience or cluster of symptoms/behaviours/experiences on the network [39]. In psychopathology networks, understanding the influence of a set of symptoms (e.g., PLEs) and how specific central symptoms relate to other behaviours (e.g., screen time) could provide insight into the intricacies of the overarching relationships between disorders and behaviours [22,31,40]. For example, considering the suggested relationship between screen consumption and PLEs, evidence indicates that engaging with interactive media (e.g., video games) may activate brain regions involved with impulse control and executive functions, stimulating in turn enhanced dopamine levels like that elicited by psychostimulants [41]. Alternatively, other forms of screen time, such as texting, may not elicit the same brain responses. Thus, better understanding the distinct network of associations between screen-time usage and psychotic experiences is paramount. Such knowledge is likely to inform interventions specifically targeting symptoms/behaviours with the greatest influence in their unique clusters (if any), as well as the whole network.

2.2. *The present study*

The primary aim of the present paper is to investigate the possible links between different types of screen usage and psychotic-like experiences. This reserach uniquely combines the methodological strengths inherent in the ABCD study, such as its large sample size and longitudinal data, with advanced network analysis methods. By analysing the complex relationships between various types of screen time consumption and different PLEs, this project aims to provide a better understanding of the underlying influences that may inform the development of psychotic disorders. Additionally, applying the LASSO algorithm (i.e. an algorithmic function reducing the impact/visibility of lower strength edges/connections) is expected to enhance the accuracy and validity of the analysis, thereby generating more reliable results [42]. The strengths of this research article lie in its comprehensive methodology and innovative approach, which can lead to significant implications for identifying and treating psychotic symptoms. By providing a better understanding of the associations between screen usage and psychotic symptoms, the study can contribute to the development of more effective prevention/intervention initiatives aimed at improving the overall wellbeing of individuals. The current study does not put forth any specific hypotheses, as network analysis is deemed most effective when approached from a data-driven and exploratory standpoint.

3. Method

3.1. *Participants*

For the current project, the data was collected in the context of the ABCD study [43]. Specifically, participants were adolescents that have been recruited across US middle schools [$N = 11{,}876$, M age = 9.92, SD age = 0.62, n males = 6196 (52.2%), n females = 5680, (47.8%)] and assessed at three different time points (T), 12 months apart. When data collection first started, participants were between 9 and 10 years old in 2017; during the last wave considered for the present research, participants were between 11 and 12 years old in 2019. The Powerly r package was used to estimate sample size. Sensitivity was set at 0.6 with a probability of 0.8, with 13 nodes and edge density set at 0.4, recommending a minimum sample size of 700 [44]. Thus, the current study is adequately powered with 10,414 participants at the smallest time point. Between Wave 1 and Wave 2, there was a retention rate of 94.5%. Between Wave 1 and Wave 3, there was a retention rate of 87.7%. Specifically, attrition/retention was inserted as an independent dummy coded variable (i.e., 0 = attrition, 1 = retention between wave one and wave three) to assess its associations with sociodemographic characteristics and key variables (via t-test). Age and sex showed no significant differences, while retention/attrition effects regarding most key variables (different digital media types and PLEs; see Table 1) demonstrated small effect sizes (Cohen's $d < 0.2$).

Table 1
T-test of demographics and key variables based on attrition.

	t	p	Cohen's d
Sex	−1.105	0.269	−0.0309
Age	−1.131	0.258	−0.0316
ScrTV	3.902	< 0.001	0.1090
ScrOnlineV	5.879	< 0.001	0.1642
ScrVG	3.857	< 0.001	0.1077
ScrText	5.829	< 0.001	0.1628
ScrSM	5.337	< 0.001	0.1491
ScrVchat	4.873	< 0.001	0.1361
PLE_5	1.806	0.071	0.0504
PLE_10	2.311	0.021	0.0645
PLE_14	−1.537	0.124	−0.0429
PLE_16	0.972	0.331	0.0271
PLE_19	0.853	0.394	0.0238
PLE_20	3.352	< 0.001	0.0936
PLE_21	1.960	0.050	0.0547

Note: ScrOnlineV: screen time playing online videos; ScrTV: screen time watching TV; ScrVG: screen time playing video games; ScrText: screen time texting; ScrVChat: screen time on video chats; ScrSM: screen time on social media; PLE 5: delusion of control; PLE 10: auditory hallucinations; PLE 14: experiential hallucinations; PLE 16: somatic delusions; PLE 19: visual hallucinations; PLE 20: struggling to concentrate; PLE 21: difficulty communicating.

3.2. *Materials*

Aside from collecting socio-demographic information the following instruments were employed for the current study.

3.2.1. *Screen time survey*

Participants' digital use was measured using the Screen Time survey [43]. Participants were asked two questions regarding their screen time: "On a typical weekday how much time do you spend doing each of the following at home?" Participants then responded with the number of hours and/or minutes they engaged in each of the following activities: (1) Watching TV or DVDs; (2) using the computer; (3) playing video games on any device (i.e., console, computer, phone); (4) Using social media (i.e., Facebook, Instagram) (5) Watching videos on platforms such as YouTube and Twitch and (6) Video calling on services such as skype and discord. The second set of questions asked about the same information during the weekends. Overall, the screen survey questions included in the ABCD dataset, aim to capture one's recollection of events/incidences (e.g., screen time in hours; the number of applications used, etc.) and not internal experiences (e.g., I felt remorse when using my mobile on a scale 1–5, where 1 is minimum and 5 is maximum). Thus, they do not constitute a scale aiming to capture a latent variable (i.e., remorse/happiness for screen usage) but rather a subjective self-report of external events. Additionally, other questions not related to the amount of time spent watching/using a screen were asked (i.e., Do you watch R-rated movies, what social media platforms do you use).

3.2.2. *Prodromal Questionnaire – Brief Child Version*

The experience and intensity/level of PLEs for participants were assessed with the Prodromal Questionnaire - Brief Child version [45]. It contains 21 items on different PLEs. Each item has a follow-up question on how distressing the experience tends to be (i.e., When this happens, I feel frightened, concerned, or it causes problems for me) measured on a Likert scale from 1 (Strongly Disagree) to 5 (Strongly Agree). Internal reliability is high (Cronbach's Alpha = 0.84; McDonald's Omega = 0.92). Acceptable validity was found through testing hypothesised associations between family history of psychosis, internalising symptoms, and neuropsychological test performance [45].

3.3. Procedure

For longitudinal data to be utilised in a timely manner a data repository, inclusive of de-identified, secondary, archival records, was used. This data was collected as part of a currently ongoing, broader ABCD study, that is investigating/assessing various aspects of children and adolescents' development. Specifically, this study aims to assess a multitude of psychological, biological, social, and neurobiological domains, throughout development into adulthood. Currently, the study has collected >3 years of data, where once a year extensive participants' information is gathered through questionnaires, cognitive assessments, biospecimen collection and magnetic resonance imaging (MRI) scan(s). The data was accessed from the US National Institute for Mental Health (NIMH) Data Archive (NDA).

3.4. Statistical analyses

A network model involving time spent on different types of digital media and Prodromal Psychosis Questionnaire symptoms were estimated for the three time points (T) using *qgraph* and *networktools* R packages. Network models are visual representations of the connections between variables. This is done via the creation of network nodes and edges, where nodes represent variables and edges are the relationship between them. Thicker, darker edges indicate stronger relationships, while the distance between nodes signifies their relevance/association to each other. Graphical Least Absolute Shrinkage and Selection Operator algorithm (g-lasso [42]) is employed to shrink small correlations/relationships to zero, to reduce the chance of false positives (i.e., Type 1 error). This allows for greater precision when making judgements about the relationships between variables and simplifies the networks.

3.4.1. Cross-sectional network stability

Once the network models have been assessed at different time points, their centrality and edge weights can be evaluated. Centrality measures are analysed by four different metrics to better understand the associations of screen time and PLEs. These measures include: a) degree (i.e., how many connections a node has to other nodes); b) betweenness (i.e., how often a node is located between the shortest path of two other nodes); c) closeness (i.e., the average number of nodes, a node must pass through, to reach all other nodes in other groupings) and; d) the 'expected influence', which also accounts for negative relationships, to better understand a node's overall influence on the whole network. Lastly, bridge values indicate the extent to which nodes act as connections between distinct network clusters (e.g. screen usage types and PLEs) and are determined using bridge expected influence indices [46,47].

To ensure accurate calculations of centrality measures, the network's stability coefficient was evaluated across the various time points. This involved identifying the maximum number of cases that could be removed from the data, while still maintaining a correlation of at least 0.7 (default) between the original network indices and those computed with altered cases. The acceptable minimum probability for this assessment was set at >0.25, with a preferable aim of >0.5 [32].

3.4.2. Cross-sectional network characteristics

Once a network is deemed stable, the *networktools* package is used to estimate the centrality, edge weight and bridge indices, and graph the network. Inferences on significant differences between centrality measures were made utilizing the centrality/edge difference tests via the *bootnet* R package. These create a confidence interval that increases in range, the lower the network stability is, with non-significant differences falling between the range.

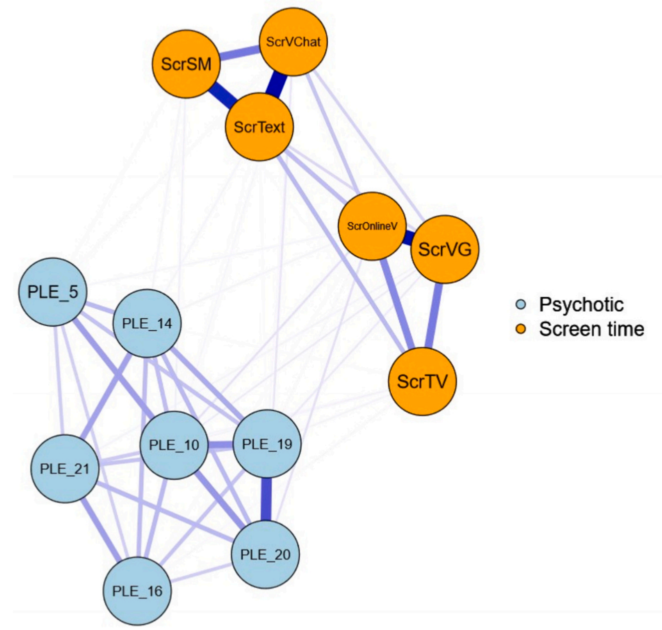

Fig. 1. Network of the PLEs symptoms and Screen Time at T1.
Note. Thicker, darker lines represent stronger connections.

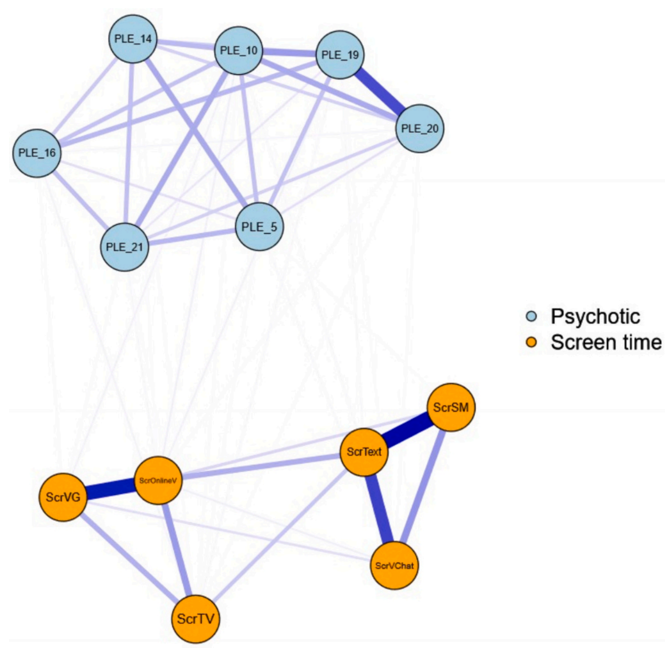

Fig. 2. Network of the PLEs symptoms and Screen Time at T2.
Note. Thicker, darker lines represent stronger connections.

3.4.3. Stability of the network across time

To compare network stability across time points, the *NetworkComparisonTest* package is employed to test differences regarding the global network structure. If a significant difference is found, differences in the global strength of nodes, edges and centrality are analysed (i.e., if networks across two time points do not differ significantly then it is pointless to analyse further [35]). An alpha level of 0.05 is used to determine significance.

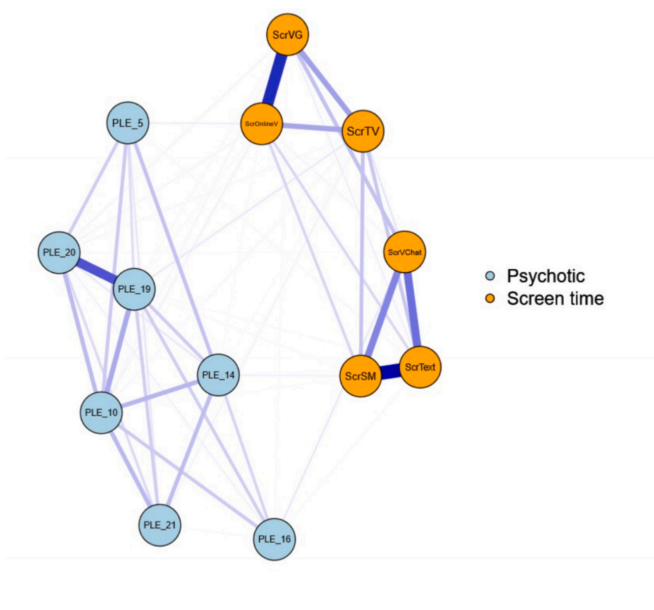

Fig. 3. Network of the PLEs symptoms and Screen Time at T3.
Note. Thicker, darker lines represent stronger connections.

4. Results

4.1. Network generation and stability

Figs. 1–3 display the three networks produced through the R studio facilitated network analyses, one for each time point (T). Tables 2–4 present edge strengths calculated for all time points. Before discussing stability, upon visual inspection of all 3 networks, the screen time variables appear to be consistently grouped into 2 different clusters. Firstly, one contains social media, texting and video chat, which can be conceptualized as a socializing cluster. Secondly, another one contains online video, video games, and TV, which can be conceptualized as an entertainment cluster.

The network at T1 showed excellent stability in terms of its basic structure (edge stability coefficient = 0.75, expected influence centrality stability coefficient = 0.75) and marginal stability regarding secondary measures of centrality (closeness centrality stability coefficient = 0.28, betweenness centrality stability coefficient = 0.05). In terms of bridges between network clusters, stability ranged from acceptable (bridge expected influence stability coefficient = 0.52), to marginal (bridge betweenness stability coefficient = 0.05, bridge closeness stability coefficient = 0.21).

These structural network characteristics were similar to the network at T2 both in terms of basic structure (edge stability coefficient = 0.75, expected influence centrality stability coefficient = 0.75) and secondary measures of centrality (closeness centrality stability coefficient = 0.13, betweenness centrality stability coefficient = 0.05). In terms of bridges between network clusters, stability ranged from acceptable (bridge

Table 2
Edge strengths across the network of time point 1.

	1	2	3	4	5	6	7	8	9	10	11	12	13
1. ScrOnlineV	–												
2. ScrTV	0.164	–											
3. ScrVG	0.344	0.183	–										
4. ScrText	0.077	0.093	0.051	–									
5. ScrVChat	0.076	0.006	0.057	0.362	–								
6. ScrSM	0.089	0.002	0	0.312	0.190	–							
7. PLE_5	0.012	0	0	0	0.007	−0.007	–						
8. PLE_10	0.035	0.016	0.022	0.002	0.011	0.018	0.131	–					
9. PLE_14	0.014	0.005	0	0.013	0	0.014	0.095	0.090	–				
10. PLE_16	0.005	0.009	0.003	0	0.002	0	0.062	0.095	0.091	–			
11. PLE_19	0.009	0.015	0.025	0.003	0.010	0	0.084	0.156	0.115	0.078	–		
12. PLE_20	0.037	0	0	0	0.031	0	0.058	0.144	0.095	0.065	0.250	–	
13. PLE_21	0	0.015	0.015	0.006	0	0	0.066	0.071	0.128	0.132	0.080	0.095	–

Note: ScrOnlineV: screen time playing online videos; ScrTV: screen time watching TV; ScrVG: screen time playing video games; ScrText: screen time texting; ScrVChat: screen time on video chats; ScrSM: screen time on social media; PLE 5: delusion of control; PLE 10: auditory hallucinations; PLE 14: experiential hallucinations; PLE 16: somatic delusions; PLE 19: visual hallucinations; PLE 20: struggling to concentrate; PLE 21: difficulty communicating.

Table 3
Edge strengths across the network of time Point 2.

	1	2	3	4	5	6	7	8	9	10	11	12	13
1. ScrOnlineV	–												
2. ScrTV	0.171	–											
3. ScrVG	0.401	0.132	–										
4. ScrText	0.133	0.091	0.033	–									
5. ScrVChat	0.023	0	0.048	0.328	–								
6. ScrSM	0.065	0	0	0.445	0.183	–							
7. PLE_5	0	0.007	0	0	0.010	0.001	–						
8. PLE_10	0.023	0.007	0.020	0.010	0	0	0.104	–					
9. PLE_14	0.004	0.004	0	0	0	0	0.145	0.117	–				
10. PLE_16	0	0.020	0.007	0	0	0	0.049	0.099	0.087	–			
11. PLE_19	0.021	0.012	0	0.009	0.004	0	0.103	0.171	0.074	0.119	–		
12. PLE_20	0.006	0.003	0	0.001	0.004	0	0.046	0.142	0.072	0.014	0.309	–	
13. PLE_21	0.012	0.002	0.007	0	0	0	0.120	0.142	0.106	0.106	0.036	0.073	

Note: ScrOnlineV: screen time playing online videos; ScrTV: screen time watching TV; ScrVG: screen time playing video games; ScrText: screen time texting; ScrVChat: screen time on video chats; ScrSM: screen time on social media; PLE 5: delusion of control; PLE 10: auditory hallucinations; PLE 14: experiential hallucinations; PLE 16: somatic delusions; PLE 19: visual hallucinations; PLE 20: struggling to concentrate; PLE 21: difficulty communicating.

Table 4
Edge strengths across the network of time point 3.

	1	2	3	4	5	6	7	8	9	10	11	12	13
1. ScrOnlineV	–												
2. ScrTV	0.160	–											
3. ScrVG	0.392	0.167	–										
4. ScrText	0.067	0.096	0.025	–									
5. ScrVChat	0.016	0.040	0.109	0.258	–								
6. ScrSM	0.070	0.102	0	0.469	0.220	–							
7. PLE_5	0.027	0	0	0.009	0	0	–						
8. PLE_10	0.022	0.014	0.015	0	0	0.004	0.004	–					
9. PLE_14	0.008	0.003	0	0.002	0	0.024	0.024	0.129	–				
10. PLE_16	0	0	0.007	−0.007	0.037	0	0	0.092	0.071	–			
11. PLE_19	0.003	0.033	0.009	0.002	0	0.006	0.059	0.153	0.089	0.085	–		
12. PLE_20	0.014	0.011	0.016	0	−0.005	0	0.087	0.120	0.038	0.021	0.309	–	
13. PLE_21	0	0.018	0	0	0	0	0.040	0.124	0.117	0.006	0.085	0.062	–

Note: ScrOnlineV: screen time playing online videos; ScrTV: screen time watching TV; ScrVG: screen time playing video games; ScrText: screen time texting; ScrVChat: screen time on video chats; ScrSM: screen time on social media; PLE 5: delusion of control; PLE 10: auditory hallucinations; PLE 14: experiential hallucinations; PLE 16: somatic delusions; PLE 19: visual hallucinations; PLE 20: struggling to concentrate; PLE 21: difficulty communicating.

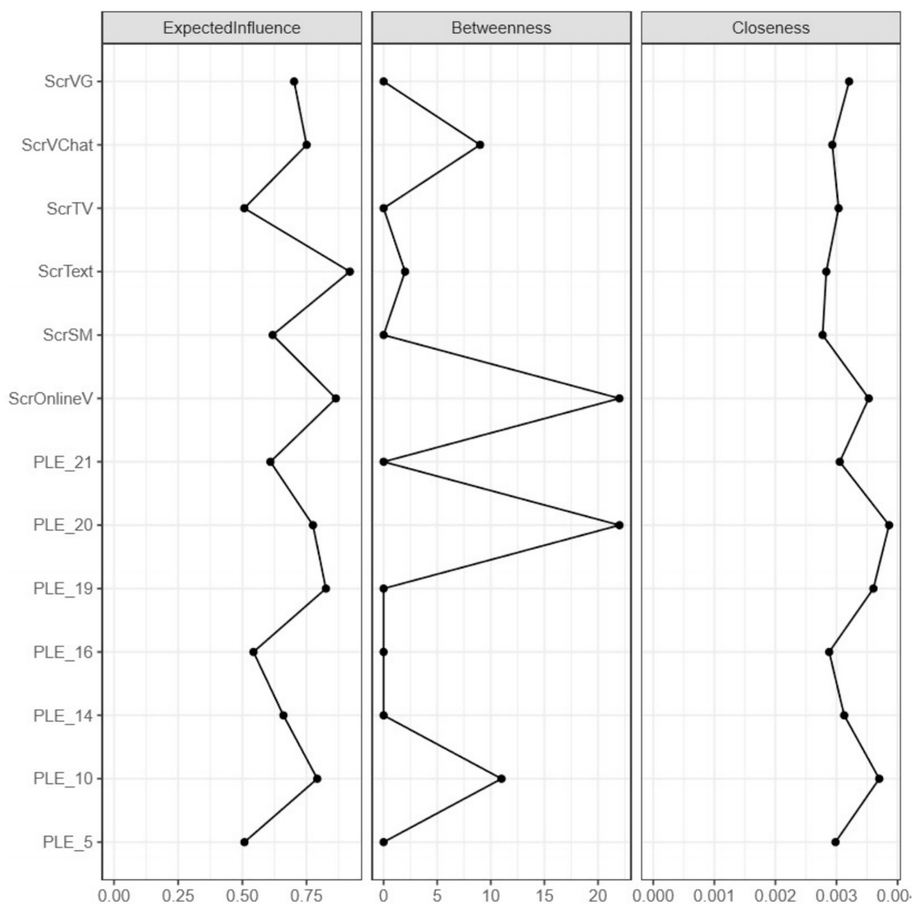

Fig. 4. Expected Influence, closeness and betweenness across all nodes at T1. Note. The horizontal axis displays standardised scores.

expected influence stability coefficient = 0.44) to insufficient (bridge betweenness =0.0, bridge closeness =0.05).

The network at T3 showed excellent stability in terms of its basic structure (edge stability coefficient = 0.75, expected influence centrality stability coefficient = 0.75) and insufficient stability for secondary measures of centrality (closeness centrality stability coefficient = 0.05, betweenness centrality stability coefficient = 0). In terms of bridges between network clusters, stability ranged from marginal (bridge expected influence stability coefficient = 0.21), to insufficient (bridge betweenness stability coefficient = 0.0, bridge closeness stability coefficient = 0.0).

After ensuring that all essential/primary stability measures were within the acceptable range (edge stability, expected influence stability, and bridge expected influence stability), further analysis of the network structures and network comparison was conducted. However, given the marginal to insufficient stability of both closeness and betweenness as measures of centrality, it was determined that the results derived from these measures cannot be reliably applied or used to make conclusions about the data. Edge and centrality stability figures have been supplied in supplementary materials.

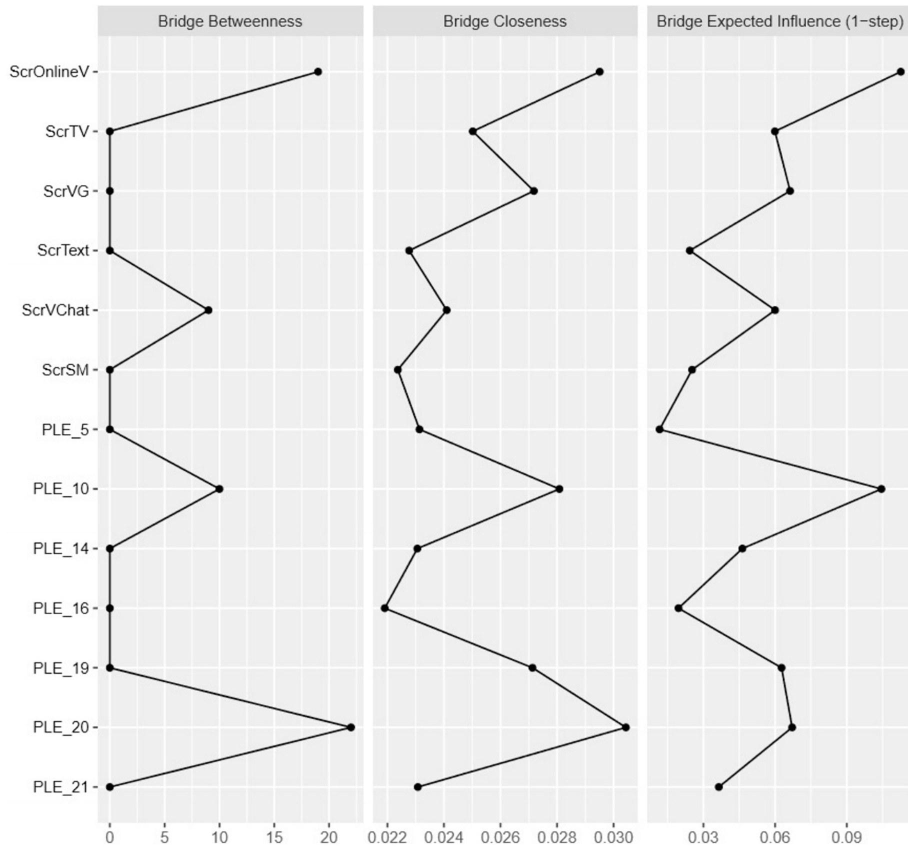

Fig. 5. Bridge Expected Influence, Betweenness and Closeness Centrality at T1.
Note. The horizontal axis displays standardised scores.

4.2. Network characteristics at time point 1

Fig. 4 depicts the expected influence, betweenness and closeness of all nodes at T1. In terms of overall centrality, texting had the most and strongest connections with other nodes. Texting had expected influence significantly greater than most nodes, except for online video and the PLEs symptom of visual hallucination (PLEs item 19). PLEs symptoms of visual & auditory hallucinations and struggling to concentrate (PLEs items 10, 19 and 20) had centrality scores significantly above other PLEs symptoms (most notably scores above symptoms of delusion; PLEs items 5 and 16). TV usage was relatively low in centrality, with a result significantly lower than every other node except delusion of control and somatic delusion (PLEs item 5 and 16 respectively; See Fig. S7 for expected influence difference tests). In terms of betweenness, online video and visual hallucinations (PLEs item 20) had the highest centrality. In terms of closeness, visual hallucinations (PLEs item 20) had the highest centrality. The edges between texting and video chat, online video and video games, texting and social media, and the PLEs symptoms of two types of visual hallucinations (PLEs items 19 and 20) were significantly stronger than those of other nodes (See Fig. S8 for edge difference tests).

4.3. Bridge characteristics at time point 1

Fig. 5 depicts bridge expected influence, closeness and betweenness centralities between screen time and PLEs. Out of all screen usage types, online video displayed substantially higher expected influence connections with the PLEs cluster than other screen types. With regards to the PLEs, auditory hallucinations, and struggling to concentrate (PLEs items 10), had a higher bridge expected influence on the screen time cluster symptoms than other PLEs. Regarding bridge betweenness, online video was highest out of the screen usage types while visual hallucinations (PLEs item 20) was the highest out of the PLEs. In terms of the proximity/closeness between nodes in the two clusters, visual hallucinations (PLEs item 20) were the highest.

4.4. Network characteristics at time point 2

Fig. 6 depicts the expected influence, betweenness and closeness of all nodes at T2. In terms of overall centrality, similar to T1 texting had the most and strongest connections with other nodes. Texting had also an expected influence significantly greater than all other nodes. In addition, online video and PLEs symptoms of visual & auditory hallucinations and struggling to concentrate (PLEs items 10, 19) had centrality scores significantly above other nodes. Similar to T1, TV usage and somatic delusion were significantly lower in centrality than the majority of nodes (See Fig. S9 for expected influence difference tests). Online video and auditory hallucinations and struggling to concentrate (PLEs item 10) had the highest betweenness value. Auditory hallucinations and struggling to concentrate (PLEs item 10) had the highest closeness score, however, every node had a similar closeness value. The edges between texting and video chat, online video and video games, texting and social media, and the PLEs symptoms of two types of visual hallucinations (PLEs item 19 and 20) were significantly stronger than those of other nodes (See Fig. S10 for edge difference tests).

-Fig. 6. Expected Influence, closeness and betweenness across all nodes at time point 2.-.

4.5. Bridge characteristics at time point 2

Fig. 7 depicts bridge expected influence, closeness and betweenness centralities between screen time and PLEs. Out of all screen usage types, online video displayed higher expected influence connections with the

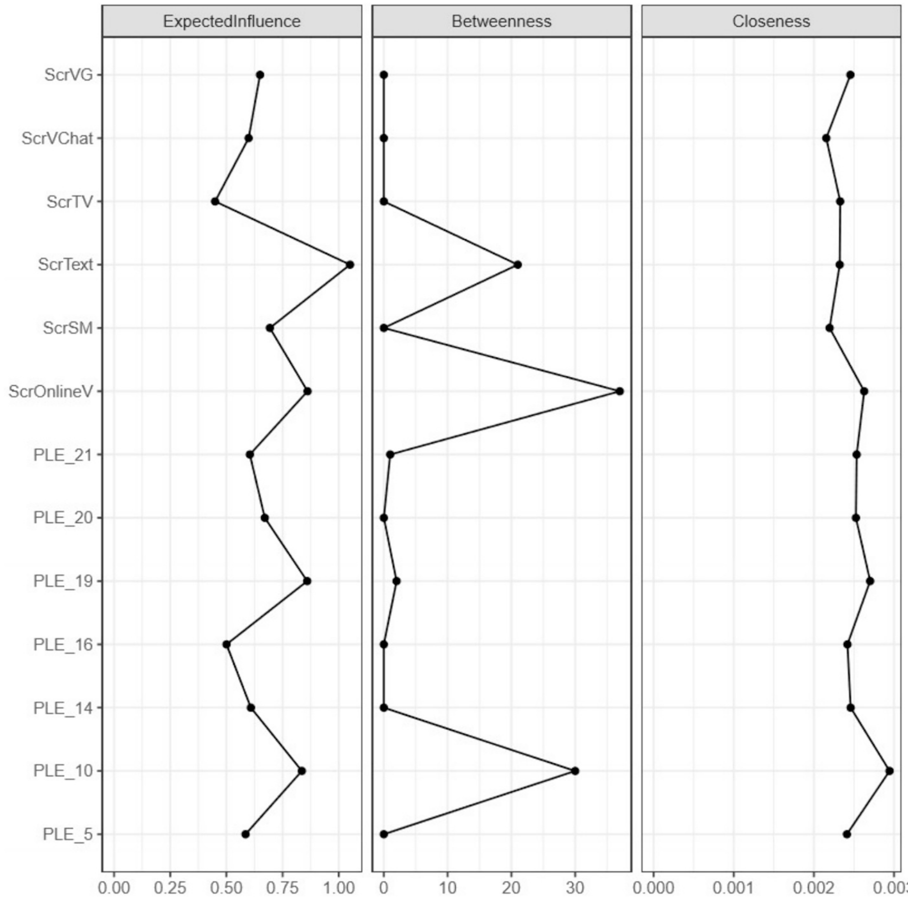

Fig. 6. Expected Influence, closeness and betweenness across all nodes at T2. Note. The horizontal axis displays standardised scores.

PLE cluster and TV being the second highest. With regards to the PLEs, auditory hallucinations and struggling to concentrate (PLEs item 10), had a higher bridge expected influence on the screen time cluster symptoms than other PLEs. Regarding bridge betweenness, online video was highest out of the screen usage types while auditory hallucinations and struggling to concentrate (PLEs item 10) was the highest out of the PLEs. Similar to betweenness auditory hallucinations and struggling to concentrate (PLEs item 10) was the highest in proximity/closeness while online video was second highest.

4.6. Network characteristics at time point 3

Fig. 8 depicts the expected influence, betweenness and closeness of all nodes at T3. Once again texting had the most and strongest connections with other nodes. Texting had an expected influence significantly greater than the majority of nodes, with the exception of social media and the PLEs symptom of visual hallucination (PLEs item 19). Somatic delusion (PLEs item 16) was significantly lower in centrality than the majority of nodes except for PLEs symptoms of delusion of control and struggle to communicate with others (PLEs item 5 and 21 respectively; See Fig. S11 for expected influence difference tests). Somatic delusion and visual hallucinations (PLEs items 16 and 19, respectively), TV and video chat had the highest betweenness values. Visual hallucinations (PLEs item 19) had the highest closeness score, however, and as per previous time-points, every node had a similar closeness value. The edges between texting and social media and online video and video games, and the PLEs symptoms of two types of visual hallucinations (PLEs item 19 and 20) were significantly stronger than those of other nodes (See Fig. S12 for edge difference tests).

4.7. Bridge characteristics at time point 3

Fig. 9 depicts bridge expected influence, closeness and betweenness centralities between screen time and PLEs. Out of all screen usage types, TV and online video displayed higher expected influence connections with the PLE cluster than other screen types. With regards to the PLEs, visual & auditory hallucinations and struggling to concentrate (PLEs items 10, 19), had a higher bridge expected influence on the screen time cluster symptoms than other PLEs. Regarding bridge betweenness, TV and video chat were the highest out of the screen usage types, while visual hallucinations and somatic delusions (PLEs items 16 and 19) were the highest out of the PLEs. In terms of the proximity/closeness between nodes in the two clusters, somatic delusions (PLEs item 16) were the highest.

4.8. Longitudinal network comparison

Lastly, a network comparison test was conducted across each time point pair (i.e., T1 and T2; T2 and T3; T1 and T3). T1 and T2 were significantly different in network structure ($M = 0.13$, $p = .005$) but not significantly different in global network strength ($p = .50$). T2 and T3 were not significantly different in network structure ($M = 0.10$, $p = .29$) and global network strength ($p = .43$). Finally, T1 and T3 were significantly different in network structure ($M = 0.16$, $p = .007$) but not significantly different in global network strength ($p = .19$).

5. Discussion

Considering the pervasive and rapidly expanding worldwide nature

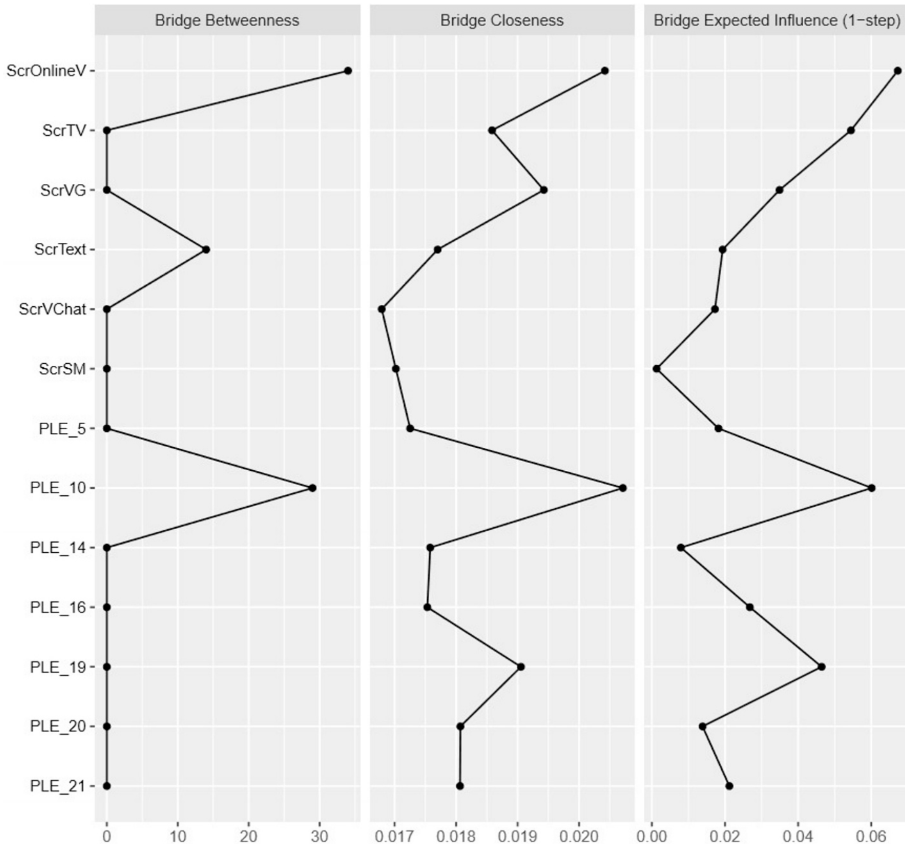

Fig. 7. Bridge Expected Influence, Betweenness and Closeness Centrality at T2.
Note. The horizontal axis displays standardised scores.

of digital media usage, it is important to investigate its impact on adolescents' development and mental health, including their PLEs [14,15,21,24]. International literature to date appears to suggest that digital/screen media consumption can have both positive and/or negative associations with general psychopathology and in particular PLEs [28,29]. It is further proposed that such contradicting relationships, with one's PLEs, may occur due to variations in screen time engagement between users, as well as the different screen usage types/applications available, and how these interact with their other individual characteristics (e.g. gender, personality traits) over time [18,20,21,28]. To address such discrepancies, the current research longitudinally assessed a normative cohort of young adolescents (>10,000), three times over three years, while emphasizing on the specific associations between their screen usage time and PLEs. Advanced longitudinal network analysis models, enriched via the LASSO algorithm, were calculated for all time points [32,36]. The findings from the network analyses provided valuable insights into the relationships between screen usage and PLEs over time.

Across all time-points, two different clusters of digital media use were revealed: a) the socializing cluster, containing of screen time consumed on social media, texting and video chat and; b) the entertainment cluster, informed by online videos, video games, and TV related screen time. Understanding the conceptualization of digital media is crucial, and research has emphasised digital media that is social is fundamentally different to media that is not [18,48]. Yet to the author's knowledge, no other papers have confirmed these clusters. Furthermore, these clusters were distinct from (i.e. did not mix/overlap with) the PLE cluster, confirming that digital media use is not directly interwoven/associated with PLEs.

Screen time spent on texting had expected influence significantly greater than most nodes examined, suggesting the potential significance of screen facilitated communication via text(s) for the entire PLEs and screen-time usage network (e.g. one's PLEs' associated discomfort may make it easier for them to communicate via text instead of face to face). Moreover, considering the independent PLEs cluster, visual and auditory hallucinations and struggling to concentrate (PLEs items 10, 19 and 20) presented to have the highest centrality/influence and thus may need to be prioritized when assessing and/or targeting PLEs among adolescents in the community. Additionally, the edges between texting and video chat, online video and video games, texting and social media, and the PLEs symptoms of two types of visual hallucinations (PLEs items 19 and 20) were significantly stronger, implying their influential role for individuals experiencing such symptoms. Therefore, they likely project as PLEs treatment case formulation priorities during this time.

Interestingly, out of all screen usage types, online video displayed higher expected influence connections with the *PLE* cluster, with TV being the second highest, implying that they might operate as likely precipitating and/or perpetuating factors of PLEs for those at risk. Furthermore, it is also possible that conspiracy theories, accessible on platforms such as YouTube and to a lesser extent TV may underpin this finding. Given that odd and magical thinking can predict having a belief in conspiracy theories [49], adolescents may be seeking out this type of content, thus spending more time watching online videos and TV. However, further research is needed to explore this hypothesis. Reversely, with regards to the *PLEs*, auditory hallucinations and struggling to concentrate (PLEs item 10), had a higher bridge expected influence on the screen time cluster symptoms than other *PLEs,* potentially indicating that individuals experiencing such symptoms may either consume digital media to ease their distress and/or, due to relating them to the content of their hallucinating experiences.

Across all metrics, PLEs items 5 & 16 (delusion of control and somatic delusion) were consistently on the lower end of centrality scores.

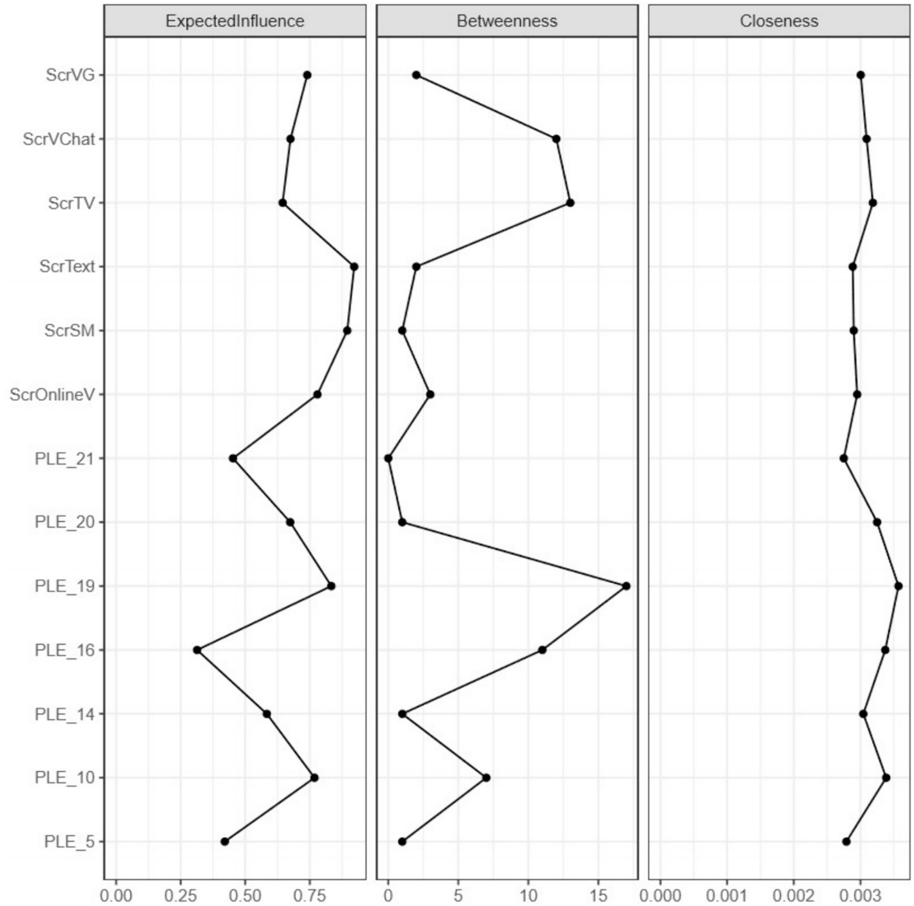

Fig. 8. Expected Influence, closeness and betweenness across all nodes at T3.
Note. The horizontal axis displays standardised scores.

Compared to PLEs items relating to hallucinations, suggesting that hallucinations have a greater influence on all PLEs and screen time usage than delusions (e.g. sub-clinical delusions may be a more normative experience and thus have weaker effect in the network examined [2]). However, not all individuals experiencing PLEs will have somatic and loss of control delusions and may have different types of delusions that were not included in the network. Therefore, the idea that hallucinations are more important to target in interventions can be only conditionally supported, yet this idea can inform future research.

Additionally, a network comparison test across the different timepoints showed that the pattern/network of associations between screen-consumption types and PLEs at 9–10 years differs significantly to those between 11 and 12 and 12–13. The latter suggests the possible role of the significant shift in cognitive functions (e.g., reasoning) initiating during the end of childhood and the beginning of adolescence, when the influence of child-like imagination, likely informing normative PLEs tends to weaken [50,51]. Overall, by providing a better understanding of the associations between screen usage and psychotic symptoms, this study can contribute to the development of timely effective interventions, that aim at improving the overall wellbeing of individuals at risk of developing a psychotic disorder, via timely targeting more influential/central behaviours.

5.1. Implications and future directions

In conclusion, the findings of the current study add to the available knowledge of PLEs in adolescents, taking simultaneously into consideration how they use digital media. Understanding the specific screen usage patterns that contribute to the development of PLEs can help in the early identification of at-risk individuals and the implementation of preventive measures. Additionally, the findings can guide the development of interventions that promote healthy screen usage habits and reduce the risk of PLEs.

It is important to note that this study approached the analysis from a data-driven and exploratory standpoint, without proposing specific hypotheses. This approach allowed for a comprehensive exploration of the complex relationships between screen usage and PLEs. However, future research could build upon these findings and formulate specific hypotheses to further investigate the underlying mechanisms at play. One suggestion would be to investigate how the different types of content affect and/or derive from the development of PLEs (i.e., educational, socializing, entertainment). Hoehe and Thibaut [20] suggest digital media used for educational purposes could have a positive effect on wellbeing compared to other content types. Therefore, taking into account the nature of the content when investigating digital media may aid in differentiating the impact of digital media on psychopathology and psychotic symptoms.

Nevertheless, the current study has limitations to be mindful of. Firstly, given the analysis was data-driven and exploratory in nature, all findings need further research to be able to generalise. Secondly, while network analysis operates on the assumption that all variables are causal and can detect the most influential/central ones considering the network as a whole, it cannot conclude any causal relationships. Lastly, self-report measures were used and thus risks of subjectivity or self-reporting errors cannot be excluded.

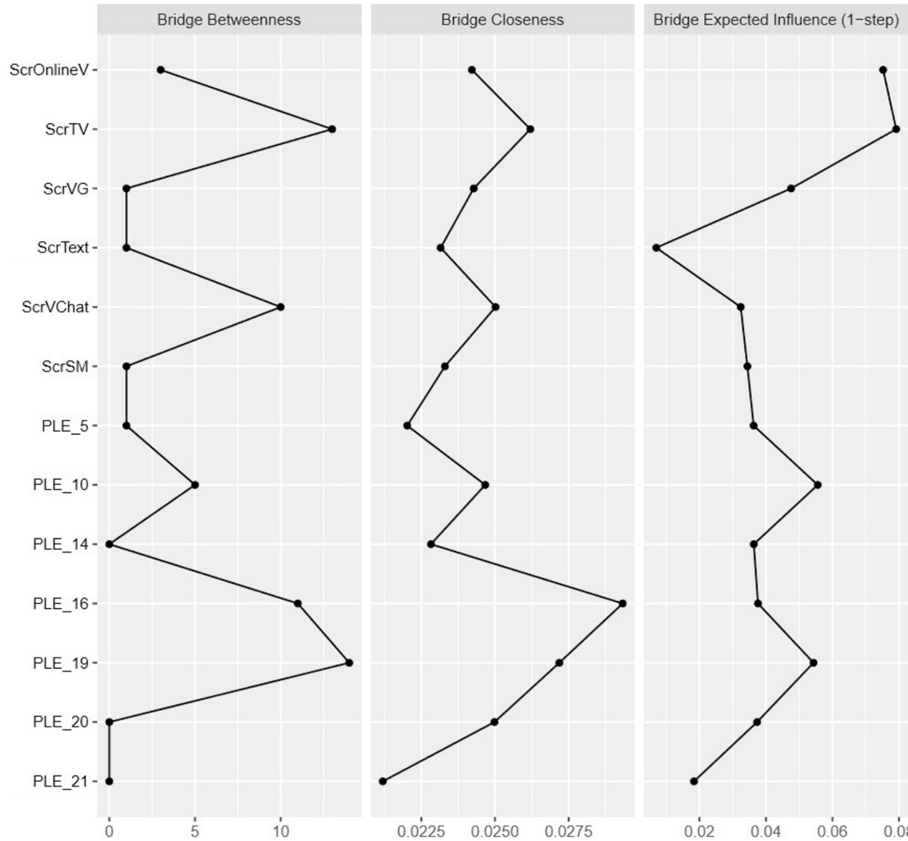

Fig. 9. Bridge Expected Influence, Betweenness and Closeness Centrality at T3.
Note. The horizontal axis displays standardised scores.

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Ethical Standards – Animal Rights

All procedures performed in the study involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. This article does not contain any studies with animals performed by any of the authors.

Informed consent

Informed consent was obtained from all participants.

Confirmation statement

Authors confirm that this paper has not been either previously published or submitted simultaneously for publication elsewhere.

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CRediT authorship contribution statement

Kaiden Hein: Writing – original draft, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Daniel Zarate:** Writing – review & editing, Supervision, Methodology, Formal analysis. **Tyrone Burleigh:** Writing – review & editing, Supervision. **Vasileios Stavropoulos:** Writing – review & editing, Writing – original draft, Supervision, Software, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors of the present study do not report any conflict of interest.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.comppsych.2024.152509.

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