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# Using Community Detection in Adolescent Media Multitasking Research. An Exploratory Study

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**ABSTRACT.** In this exploratory study, we used the community detection approach to complex networks analysis to analyze temperamental and executive functioning profiles of media multitaskers in early adolescence. Media multitasking is particularly intense in adolescence (Smahel et al., 2020), with implications for short- and long-term functioning (van der Schuur et al., 2015, 2020). Temperament and executive functioning are central for self-regulation and adaptation during adolescence (Rothbart et al., 2011; Blakemore & Choudhury, 2006; Atherton et al., 2019) and are related to media multitasking (van der Schuur et al., 2015; Rogobete et al., 2021, 2024). Participants were a group of early adolescents (11 - 14.5 years old). Community detection yielded 3 distinct groups of individuals, characterized by various combinations of media multitasking frequency, temperamental traits and executive functioning problems. Relevant similarities and differences have been identified between these groups using further quantitative analyses. Results are discussed in terms of the dynamics between temperament, executive functioning and media multitasking behavior during adolescence – an important period for the development of self-regulation and the formation of media habits. Importantly, this exploratory study offers preliminary evidence supporting the usefulness of community detection in complex network analysis for investigating the dynamics of media multitasking behavior.

**Keywords:** complex network analysis, media multitasking, early adolescence, temperament, executive functioning

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## INTRODUCTION

In this study we aimed to use a data-driven approach that is novel in media use studies - community detection in complex networks - to explore the temperamental and executive functioning (EF) profiles of media multitaskers in early adolescence. We wished to illustrate how this method can be used to uncover media multitasking (MM) profiles characterized by a *combination* of individual traits while avoiding bias associated with generating a-priori MM based on continuous MM scores (e.g., Ophir et al., 2009; Shin et al., 2020). By observing how these characteristics and MM co-occur in less biased, naturally emerging groups, we might identify EF and temperamental profiles that are likely to accompany high levels of MM, believed to have a potential negative effect on adolescent functioning (e.g., Baumgartner et al., 2018; van der Schuur et al., 2020), and facilitate timely intervention. Identifying distinct profiles that accompany low/moderate MM levels might also help us gain insight into factors that favor positive media habits, thus informing adequate digital education and prevention of problematic behaviors. Last, by analyzing how temperament and EF vary with MM scores between groups, we might gain some insight into a potential dynamic between these characteristics and MM, as they change within individuals.

### Media Multitasking, Temperament and Executive Functioning

MM involves performing two or more activities simultaneously, out of which at least one entails a media device/content (Parry & Roux, 2021). MM generally involves multiple media activities (M-MM; e.g., playing video-games while watching YouTube) or multiple media and non-media activities (e.g., listening to music while eating; Parry & Roux, 2021). When non-media activities involve school tasks, we speak about academic MM (A-MM; e.g., watching TV during homework; van der Schuur et al., 2020). While it has been studied at various ages (Baumgartner & Sumter, 2017; van der Schuur et al., 2015), MM is particularly intense in adolescence (Smahel et al., 2020). This makes media a pervasive environmental factor during a period of increased neuroplasticity and environmental permeability (Galván, 2021), with potential implications for adolescent short- and long-term functioning and development (Baumgartner et al., 2018; van der Schuur et al., 2015, 2020) - thus, an important target for research.

Regardless of age, MM emerges within a complex system shaped by interconnected factors, often studied separately in relation to MM to assess their unique contributions. Many of these factors have distinct yet interrelated dimensions (Miyake et al., 2000), which can be linked to MM in various ways (predictors, outcomes or both). Temperament (e.g., Sanbonmatsu et al., 2013) and EFs (e.g., May & Elder, 2018; van der Schuur et al., 2015) are two important examples of such factors.

**Temperament** refers to biological differences in motor, emotional and attentional reactivity to internal and external stimuli, as well as in the processes involved in self-regulating this reactivity (Putnam et al., 2001). It has been shown to be quite stable across development (Atherton et al., 2019; Rothbart et al., 2011) and related to overall functioning in numerous domains (Vohs & Baumeister, 2016; including MM, Sanbonmatsu et al., 2013). Temperamental characteristics influence self-regulation (Rothbart et al., 2011) and motivation for behavior (Atherton et al., 2019), which are likely to further influence behavioral choices. This relationship is likely to be relevant for media behavior during adolescence, as access to personal media devices increases and parental monitoring decreases (Top, 2016), leaving adolescents more in charge of their media habits.

Temperament might be relevant for MM in several ways. Firstly, MM may be used by individuals with increased temperamental negative affectivity as a way of upregulating positive (Popławska et al., 2021) or downregulating negative emotions (García-Oliva & Piqueras, 2016; Popławska et al., 2021). Secondly, MM may be a way of creating physical or mental stimulation for individuals higher in sensation seeking or activity levels (Duff et al., 2014). Thirdly, individuals lower in temperamental effortful control (who display lower self-regulation), may MM more because they have more difficulties controlling media use, which might also make them more susceptible to problematic media behaviors/addiction (Li et al., 2016). Fourth, MM may be performed strategically by individuals with better effortful control, in an attempt to improve cognitive functioning (Kononova & Yuan, 2017; Popławska et al., 2021) or performance on school (Throuvala et al., 2019) or work tasks (Perks & Turner, 2019). Some evidence indicates a differential relationship between different temperamental traits and different types of MM during adolescence. In a recent study, lower effortful control significantly predicted greater A-MM (but not M-MM), while higher negative affectivity and lower sociability predicted more frequent M-MM in early adolescents (Rogobete et al., 2024).

**Executive Functions** are group of cognitive processes that support the top-down regulation of goal-directed behavior (Miyake et al., 2000). Inhibitory control, working memory (WM) and task shifting are the most frequently studied EFs (Miyake et al., 2000). During adolescence, these processes develop in tandem with a cognitive system that undergoes significant reorganization, under the joined influence of biological and environmental factors (Blakemore

& Choudhury, 2006). Given their role in self-regulation and their intertwinement with neural maturational processes, EFs might be factors that both shape and are shaped by media interaction. Thus, EFs have been widely studied in relation to various aspects of media use, including MM (May & Elder, 2018; van der Schuur et al., 2015). Findings point towards multiple potential roles of EFs for MM. Longitudinal results from adolescent samples show increased attentional and EF difficulties as *outcomes* of more frequent M-MM or A-MM (Baumgartner et al., 2018; van der Schuur et al., 2020). Meta-analyses reveal that more frequent MM is associated with worse cognitive outcomes, although effects sizes tend to be moderate or small (e.g., Parry & Roux, 2021). EFs can also constitute proximal *antecedent* factors that can trigger MM. On the one hand, individuals with better EFs, such as greater WM capacities (Murphy & Creux, 2021) and more effective task-switching abilities (Elbe et al., 2019), might be more confident in their ability to MM effectively and, thus, engage in this behavior more frequently, irrespective of their objective multitasking ability. On the other hand, MM may be the result of *situational lapses* in self-regulation that arise from *poor pre-existing EFs* (e.g., Minear et al., 2013), which might make individuals more vulnerable to intrusions from media related stimuli in the environment (Ophir et al., 2009). Thus, both temperament and EFs can contribute to and be affected differently by MM behavior.

It is important to note that MM behavior itself has been shown to be heterogenous (Wiradhany & Baumgartner, 2019). People are more likely to combine some activities when MM instead of others (Wiradhany & Baumgartner, 2019) and distinct types of MM are associated differentially with certain variables (Rogobete et al., 2024). For example, lower inhibitory control predicts more frequent M-MM, but not A-MM (Rogobete et al., 2024).

Since putting together these separate contributions to diverse types of MM and their outcomes into a coherent theory is challenging at this point, a useful approach might be to analyze relevant traits, their dimensions and MM behavior *collectively*, through profiles. This approach considers the contribution of multiple individual traits and explores how they coexist in relation to one another and to various MM types. The community detection approach in complex network analysis is a useful method of exploring such MM profiles.

### Complex Network Analysis and community detection

A complex network is a graphic that contains nodes and a series of edges that connect them (Albert & Barabasi, 2001). Usually, nodes represent variables, and the edges reflect the relationships between them. Since it was introduced in psychological research (Borsboom & Cramer, 2013), Complex Networks

Analysis has been used to investigate intricate phenomena that involve dynamic relationships between variables: exploring the structure and interactions among psychological disorder symptoms (Borsboom & Cramer, 2013) and etiological factors (Isvoranu et al., 2017), applications of theoretical models in health psychology (Hevey, 2018), exploring changes in the structure of complex cognitive abilities (e.g., executive functioning) across the lifespan (e.g., Menu et al., 2024) or in varying populations (Karr et al., 2024), modelling personality structures and their correlates (e.g., Schouw et al., 2020). In media use studies, network analysis has been used to a lesser extent but yielded relevant results. It has proven useful in uncovering the most likely combinations of media activities when MM (e.g., Fisher et al., 2023; Wiradhany & Baumgartner, 2019), their relationship to various outcomes, such as attentional functioning (e.g., Fisher et al., 2023), as well as the structure of social networks on social media (Malik & Abid, 2022).

There are multiple ways of generating and organizing complex networks (Albert & Barabasi, 2001; Borsboom & Cramer, 2013). Of them, the *community detection approach* is adept at identifying sets of nodes that have aggregated into groups (i.e., communities) with specific common properties (Fortunato, 2010). When generating networks using this approach, individuals, rather than variables, constitute the nodes and the edges' characteristics reflect the *similarity* between them, as it emerges from various behavioral and individual measures. Thus, more similar individuals are positioned closer to each other in the network, have stronger and more frequent edges between them and, thus, constitute a community (Fortunato, 2010). In psychology, this approach has been used to extract and analyze psychiatric subtypes (Agelink van Rentergem et al., 2023), to study the structure and function of brain networks (Ashourvan et al., 2019) or to explore social networks characteristics (Bedi & Sharma, 2016). To our knowledge, it has not been employed so far in media use studies, except for some applications on social media networks (e.g., Naik et al., 2022).

Given the increasing sophistication and usefulness of network analysis and community detection in psychological research, our aim was to explore how this method could be used to generate profiles involving MM and its correlates during early adolescence. An important advantage of this approach it that it does not rely on specifying a-priori weights for the dimensions that drive community formation (Newman, 2006). Rather, the emerging communities reflect the underlying structure of the data along the specified dimensions. Thus, participants are expected to organize inside the network and into communities based on the underlying similarities in their responses on relevant measures that bear equal weight, rather than based on experimenter expectations or reasoning. In contrast, current MM studies often compare two- or three-MM groups that have been generated based on their scores on a MM measure, using a cut-off chosen by the experimenter (e.g., first and last 10% of the Media Multitasking Index scores, Ophir et al., 2009). This method might lead to variable results because of inconsistency in application (e.g., quartile split, Shin et al., 2020 vs. over and below 1SD, Ophir et al., 2009) or sample characteristics (e.g., homogenous MM scores).

Thus, in the present study, we used the community detection approach to explore temperamental and EF profiles that accompany MM behavior in a sample of early adolescents. Provided that there are multiple MM user profiles, characterized by specific combinations of MM behavior, temperamental dimensions and EF challenges, we expected the analysis to yield multiple, fairly delimited communities, that differ in their levels of MM, EFs and temperamental characteristics.

## METHODS AND MATERIALS

### Participants

Participants in this study were a group of early adolescents ($N = 41$) that come from middle-class families in three urban areas in Romania. The group consisted of 21 females and 20 males ($N = 41$), aged between 11 and 14.5 years-old ($M = 12.43$, $SD = 0.93$), for which parental consent was obtained. This group is part of a sample that participated in a larger study with additional measures (see *reference anonymized* for complete sample description).

### Instruments

**Media Multitasking**. The Media Multitasking Measure – Short Form (Baumgartner et al., 2017; Rogobete et al., 2021 for Romanian translation) was used to measure time spent with technology (TT) and two types of MM – with other media activities (M-MM) and academic MM (A-MM). In Section 1 (TT) participants reported the time they spent watching TV, sending messages, and browsing social media sites on an average day in the last two weeks (1 - not at all, 8 - more than 5 hours). hours). Section 2 (MM) targets the four most frequently combined media activities in adolescence. Primary activities were watching TV, sending messages, and browsing social media sites, while listening to music was used only as a secondary activity. To measure M-MM, participants reported for each primary activity how often they engaged in the three other media activities at the same time (1 – never, 4 – very often). For A-MM, participants reported how often they engaged in the four media activities above during school activities (1 – never, 4 – very often). The Media Multitasking Index for Media activities (M-MM, $\alpha$ *Cronbach* = .79) was the average of three sub-scores obtained by averaging the MM responses for each of the three primary media activities (average MM frequency across media activities). The same was done for the Media Multitasking Index for school activities (A-MM, $\alpha$ *Cronbach* = .65; average MM frequency during school activities such as online classes). See descriptive statistics and reliability indicators in Table 1 and correlations with other measures in Table 2.

**Executive Functioning problems**. Five subscales of the Behavior Rating Inventory of Executive Function—Self Report (BRIEF; Guy et al., 2004) were used to measure self-reported EF problems (overall $\alpha$ *Cronbach* = .94): Inhibition, Shifting, Emotional Control, Monitoring and Working Memory. Adolescents indicated how often during the last week they encountered specific problems in day-to-day aspects related to the five EF domains (1—never; 3—often). Separate sub-scale scores were obtained by averaging the values of each scales' corresponding items. Higher scores on these subscales indicate greater difficulties in their respective EF dimension (descriptives and correlations in Tables 1 and 2).

**Temperament**. The Early Adolescence Temperament Questionnaire (EATQ – SR; Ellis & Rothbart, 1999; translated by Țincaș et al., 2010) was used to measure four temperamental dimensions: Effortful Control (EC), Surgency (SUR), Negative Affectivity (NA) and Affiliativeness (AFF). Due to questionnaire length and time constraints, 10 of the 13 sub-scales were used (80 items): *EC*: Activation Control, Attention and Inhibitory Control; *SUR*: Activity Level and High Intensity Pleasure; *NA*: Fearfulness and Frustration; *AFF*: Affiliativeness, Low Intensity Pleasure and Perceptual Sensitivity. Participants reported how often each statement was true for themselves (1 - almost never true to 5 - almost always true). To calculate the scores, we first averaged the items corresponding to each sub-scale. The final score for each overall dimension was the average of the sub-scores for the corresponding sub-scales. Higher scores reflect a higher tendency to behave in line with each dimension's specificity (descriptives and correlations in Tables 1 and 2).

**Control variables**. Age and TT were used as control variables for group comparisons. TT represents the average amount of time spent with media activities in a typical day and was the average of participants' scores (1–8) for the three media activities included in Section 1 of the MUQ (descriptives and correlations in Tables 1 and 2).

**Table 1.** *Descriptive statistics and reliability indicators for all measures provided fc the whole sample and each emerging community in the complex network analysis.*

| | **LMM** (*n* = 15) | | **IMM** (*n* = 15) | | **HMM** (*n* = 11) | | **Whole sample** (*N* = 41) | | |
|---|---|---|---|---|---|---|---|---|---|
| | ***M*** | ***SD*** | ***M*** | ***SD*** | ***M*** | ***SD*** | ***M*** | ***SD*** | ***α Cronbach*** |
| Age (months) | 147.13 | 12.69 | 149.13 | 10.58 | 152.27 | 10.15 | 149.24 | 11.20 | - |
| Time Technology (TT) | 2.76 | 0.91 | 3.49 | 1.05 | 2.97 | 1.06 | 3.08 | 1.03 | .57 |
| M-MM | 1.59 | 0.41 | 1.99 | 0.36 | 2.47 | 0.38 | 1.98 | 0.51 | .79 |
| A-MM | 1.32 | 0.42 | 1.57 | 0.31 | 2.32 | 0.39 | 1.68 | 0.55 | .65 |
| EF-Inhibition | 1.39 | 0.17 | 1.86 | 0.25 | 2.08 | 0.28 | 1.75 | 0.37 | .81 |
| EF-shifting | 1.34 | 0.27 | 1.66 | 0.32 | 1.98 | 0.14 | 1.63 | 0.36 | .80 |
| EF-emotional control | 1.41 | 0.20 | 1.79 | 0.30 | 2.10 | 0.43 | 1.73 | 0.41 | .81 |
| EF-monitoring | 1.48 | 0.36 | 1.89 | 0.46 | 1.98 | 0.32 | 1.77 | 0.44 | .72 |
| EF-working memory | 1.36 | 0.23 | 1.67 | 0.28 | 2.11 | 0.33 | 1.67 | 0.40 | .87 |
| T-EC | 3.93 | 0.35 | 3.16 | 0.26 | 3.01 | 0.27 | 3.40 | 0.50 | .82 |
| T-SUR | 3.09 | 0.61 | 3.71 | 0.52 | 3.22 | 0.42 | 3.35 | 0.59 | .77 |
| T-NA | 3.03 | 0.36 | 3.46 | 0.37 | 3.79 | 0.35 | 3.39 | 0.47 | .60 |
| T-AFF | 3.55 | 0.47 | 3.71 | 0.41 | 3.28 | 0.67 | 3.54 | 0.53 | .81 |

*Note*. M-MM = media multitasking with other media activities; A-MM = academic media multitasking; EF = executive functioning; T = temperament; EC = Effortful Control; SUR = Surgency; NA = Negative Affectivity; AFF = Affiliation. LMM = light media multitaskers; IMM = intermediate media multitaskers; HMM = heavy media multitaskers.

**Table 2.** *Intercorrelations between the 11 measures and control variables in the whole sample*

| | **Age (months)** | **Time Tech-nology (TT)** | **M-MM** | **A-MM** | **EF-In-hibi-tion** | **EF-shift-ing** | **EF-emo-tional control** | **EF-moni-toring** | **EF-WM** | **T-EC** | **T-SUR** | **T-NA** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Time Technology (TT)** | -.156 | | | | | | | | | | | |
| **M-MM** | .068 | .351* | | | | | | | | | | |
| **A-MM** | .211 | -.045 | .570** | | | | | | | | | |
| **EF-Inhibition** | .316* | .129 | .636** | .526** | | | | | | | | |
| **EF-shifting** | .165 | .138 | .588** | .429** | .641** | | | | | | | |

| | Age (months) | Time Technology (TT) | M-MM | A-MM | EF-Inhibition | EF-shifting | EF-emotional control | EF-monitoring | EF-WM | T-EC | T-SUR | T-NA |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **EF-emotional control** | .174 | .355* | .548** | .394* | .615** | .700** | | | | | | |
| **EF-monitoring** | .298 | .194 | .417** | .286 | .668** | .557** | .537** | | | | | |
| **EF-WM** | .171 | -.016 | .629** | .674** | .757** | .725** | .545** | .527** | | | | |
| **T-EC** | .102 | -.151 | -.457** | -.476** | -.660** | -.547** | -.526** | -.494** | -.545** | | | |
| **T-SUR** | .073 | .269 | .125 | .098 | .223 | .199 | .061 | .154 | .324* | -.102 | | |
| **T-NA** | -.168 | .134 | .512** | .210 | .458** | .574** | .557** | .331* | .433** | -.576** | .002 | |
| **T-AFF** | -.124 | .098 | -.251 | -.238 | -.237 | -.097 | .056 | -.191 | -.208 | .066 | .310* | .187 |

*Note*. See variable abbreviations in Table 1 note. ** - significant at the $p$ = 0.01 level (2-tailed); * - significant at the 0.05 level (2-tailed);

### Procedure

Required ethical approval was obtained for this study in accordance with doctoral research requirements at Babeș-Bolyai University. Parents enrolled their child in the study and offered informed consent via an online link. Given questionnaires length (≈ 1.5h required in total), teenagers completed them online, in two different days that were programmed beforehand with the parent. Questionnaires were password protected and anonymized with individual codes to ensure data protection. If questionnaires were not completed by the end of the day, a reminder was sent the next day.

### Data analysis

We first modelled the network and identified the emerging communities. To ascertain that the resulting groups were not a mere statistical artifact, we calculated modularity indicators for the network (i.e., how separate emerging communities are) and conducted a MANCOVA in which we compared all emerging groups on the 11 measures of EFs, Temperament and MM, controlling for age and TT.

Modelling the network. To model the network, we used 11 scores: 5 EF problems domains, 4 temperamental dimensions and 2 MM types. Each participant was coded as an entry in a Support Vector Machine[3] (SVM; Cortes & Vapnik, 1995), where it was represented as a vector that combined the 11 scores (considered coordinates). Based on the integration of these coordinates, the SVM model represented participants as nodes and positioned similar ones closer to each other in the vectorial space. The links between these nodes were based on the distance between the entries in the SVM space. A link between two nodes (A and B) was created if the SVM cosine distance between them was lower than the average distance between the first node (i.e., A) and all other close nodes. In this way, the generated complex network was pruned in such a way to contain only meaningful (i.e., close) links between the nodes and to exclude any link that may have been encoded for two nodes that are not meaningfully close to each other. The SVM model was generated using Python (version 3.8) framework *gensim* (Rehurek & Sojka, 2011) and was encoded as a complex network using *Networkx* (https://github.com/networkx/networkx). To extract and visualize the emerging communities, we applied the algorithm proposed by Lambiotte & Panzarasa (2009) from the Gephi tool (Bastian et al., 2009, March). To validate the quality and distinctiveness of the emerging communities we calculated the modularity score for the network Q = [-1,+1] (Newman, 2006). A positive modularity score indicates a strong network structure, with stronger interconnected nodes inside the community than expected by chance (i.e., high similarity between the participants in a group). A negative modularity score indicates poor network structure, with weaker interconnected communities than expected by chance (Newman, 2006). Initial descriptive statistics and MANCOVA were conducted using SPSS version 26.0.

## RESULTS

Initial descriptive statistics show moderate levels of M-MM and relatively low levels of A-MM in the sample (Table 1). EF problems in all five domains

[3] An SVM is a machine learning technique, based on optimization algorithms and linear algebra, that helps classify observations (or individuals) in large datasets into multiple classes, based on multiple *features* of those observations. It helps create a multi-dimensional virtual space onto which observations can be mapped (see Cortes & Vapnik, 1995 for details).

seem to reach a moderately high level and all temperamental dimensions are balanced across the sample. No outliers were found in the initial data screening. As for control variables, no gender differences were found for our target variables. Age was significantly correlated with EF problems in inhibition ($r$ = 32, $p$ = .04) and TT was significantly correlated with M-MM ($r$ = .35, $p$ = .02) and with EF problems in emotional control ($r$ = .36, $p$ = .02). Thus, analyses were only controlled for age and TT.

### Community detection complex network analysis

Three distinct structures (communities; $n_1$=15, $n_2$=15, $n_3$=11) emerged in the networks analysis (see Figure 1 for a graphical representation of the network structure). The modularity score for the network was $Q$ = 0.51, which reflects adequate distinctiveness between our three emerging communities (Newman, 2006).

### Group descriptive profiles

Descriptive data for all three groups on the 11 dimensions and 2 control variables are presented in Table 1 (see also Figure 2). For ease of communication, the groups were termed based on their MM scores: group 1 - light MMs (LMMs), group 2 - intermediate MMs (IMMs) and group 3 - heavy MMs (HMMs). The three groups did not differ significantly in age ($F$ (2, 38) = 0.658, $p$ = .52), nor in TT ($F$ (2, 38) = 2.101, $p$ = .14).

LMMs scored lowest on both MM types, all five EF problems domains and lowest on two temperamental dimensions: Surgency, Negative Affectivity. This group scored highest on the Effortful Control dimension and had moderate scores on Affiliativeness. IMMs were characterized by intermediate scores on both MM types, all EF problem domains and the Effortful Control and Negative Affectivity temperamental dimensions. This group scored highest on the Surgency and Affiliativeness temperamental dimensions. HMMs scored highest on both MM types and reported the most frequent EF problems on all 5 domains. They scored lowest on temperamental Effortful Control and Affiliativeness and highest on Negative Affectivity, while displaying moderate levels of Surgency.

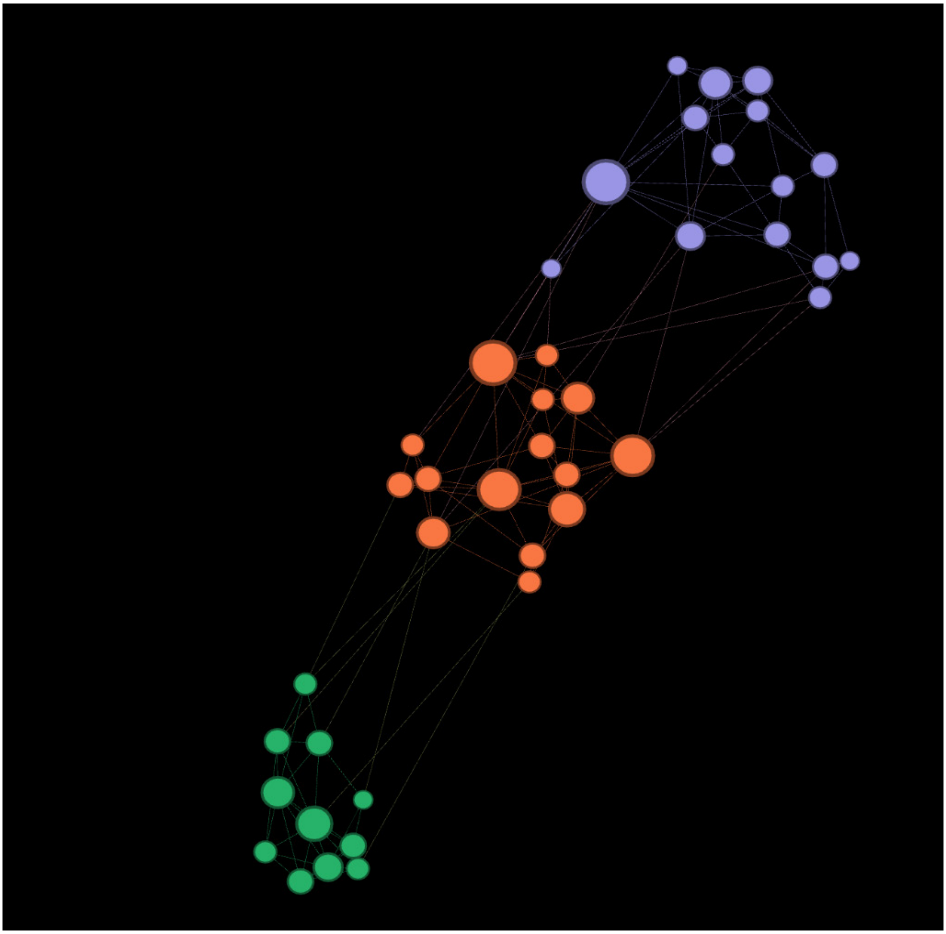

***Figure 1.*** Visualization of the complex network structure and its three emerging communities.

*Note.* Green (bottom) = Heavy Media Multitaskers (HMMs); Orange (middle) = Intermediate Media Multitaskers (IMMs); Purple (top) = Light Media Multitaskers (LMMs)

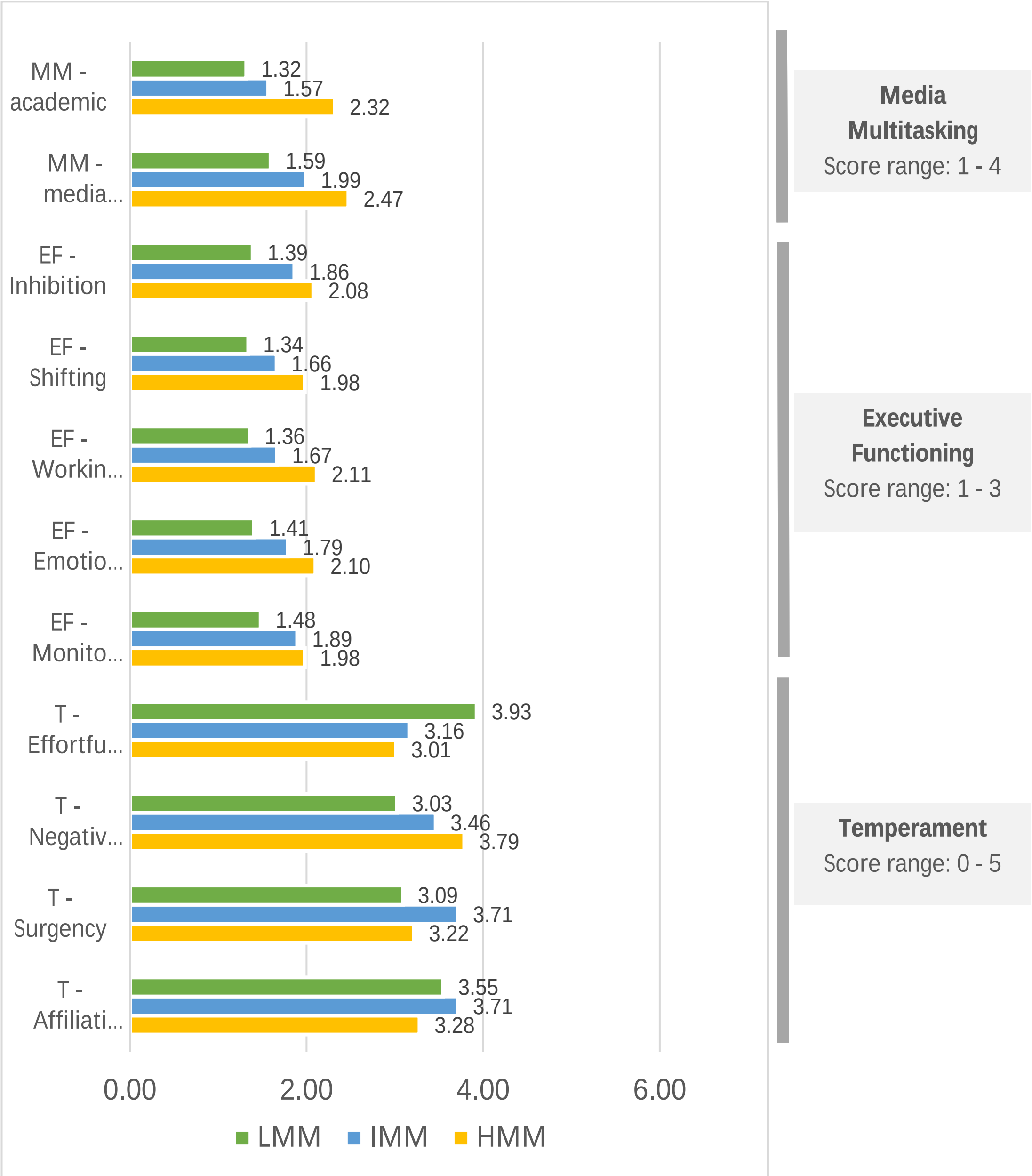


**Figure 2.** *Descriptive mean scores on the 11 dimensions that contributed to the community generation in the complex network analysis for each of the three emerging groups.*

**MANCOVA**

In the MANCOVA, the group to which each participant belonged, as indicated by the community detection algorithm, was the fixed factor (Complex Network Group) and the two MM Indexes, the five EF problems domains and the four temperament dimensions were the dependent variables. Age and TT were control variables. Multivariate analyses using Pillai's Trace showed a significant effect of Complex Network Group ($V$ = 1.44, $F$ (22, 54) = 6.255, $p$ < .000, *partial* $h^2$ = .718). Significant between-subject effects were found for all dependent variables, apart from Affiliativeness (Table 3).

**Table 3.** *Results of between subjects effects test for the 11 variables used to aggregate the communities*

| Score | $F$ (2, 36) | $p$ | *partial* $h^2$ |
|---|---|---|---|
| **M-MM** | 17.386 | .000 | .491 |
| **A-MM** | 21.722 | .000 | .547 |
| **EF-Inhibition** | 26.331 | .000 | .594 |
| **EF-shifting** | 16.145 | .000 | .473 |
| **EF-emotional control** | 14.785 | .000 | .451 |
| **EF-monitoring** | 4.640 | .016 | .205 |
| **EF-WM** | 22.389 | .000 | .554 |
| **T-EC** | 44.080 | .000 | .710 |
| **T-SUR** | 4.005 | .027 | .182 |
| **T-NA** | 17.512 | .000 | .493 |
| **T-AFF** | 1.927 | .160 | .097 |

*Note.* See variable abbreviations in Table 1 note.

*Pairwise comparisons.* To detangle the between-group differences, we conducted pairwise comparisons using Sidak test (Table 4**).** These analyses showed significant differences on M-MM between LMMs and HMMs ($p$ < .000) and between IMMs and HMMs ($p$ = .001), but not between LMMs and IMMs ($p$ = .136). The same is true for A-MM ($p_{LMM-HMM}$ < .000, $p_{IMM-HMM}$ < .000, $p_{LMM-IMM}$ <.224). HMMs had significantly greater scores than LMMs and IMMs on both MM indexes.

Regarding EF problems, all three groups were significantly different from each other on Shifting ($p_{LMM-IMM}$ = .023, $p_{LMM-HMM}$ < .000, $p_{IMM-HMM}$ = .025) and WM ($p_{LMM-IMM}$ = .012, $p_{LMM-HMM}$ < .000, $p_{IMM-HMM}$ = .002). For both EF domains, HMMs scored highest, followed by IMMs and LMMs. For EF Inhibition, LMMs reported significantly fewer problems than both IMMs and HMMs ($p < .000$). The difference between IMMs and HMMs was non-significant ($p = .111$). For EF Emotional Control, both LMMs ($p < .000$) and IMMs ($p = .012$) reported fewer problems than HMMs. For EF Monitoring, LMMs scored significantly lower than HMMs ($p = .023$), but not IMMs ($p = .071$). HMMs and IMMs did not differ significantly ($p = .919$).

**Table 4.** *Results of pairwise comparisons between the three emerging groups on all 11 measures used to generate the complex network*

| Dependent Variable | Compared groups | | *Mean Difference* | *SE* | $p_{Sidak}$ | $CI_{Low}$ | $CI_{Up}$ |
|---|---|---|---|---|---|---|---|
| **M-MM** | LMM | IMM | -.284 | .138 | .136 | -.631 | .063 |
| | | HMM | -.849** | .145 | .000 | -1.213 | -.485 |
| | IMM | HMM | -.565** | .145 | .001 | -.929 | -.201 |
| **A-MM** | LMM | IMM | -.263 | .147 | .224 | -.630 | .104 |
| | | HMM | -.990** | .154 | .000 | -1.375 | -.605 |
| | IMM | HMM | -.727** | .154 | .000 | -1.112 | -.341 |
| **EF-inhibition** | LMM | IMM | -.451** | .089 | .000 | -.674 | -.228 |
| | | HMM | -.652** | .093 | .000 | -.886 | -.418 |
| | IMM | HMM | -.201 | .094 | .111 | -.435 | .033 |
| **EF-shifting** | LMM | IMM | -.297* | .105 | .023 | -.560 | -.033 |
| | | HMM | -.627** | .110 | .000 | -.904 | -.351 |
| | IMM | HMM | -.331* | .110 | .015 | -.607 | -.054 |
| **EF-emotional control** | LMM | IMM | -.278 | .113 | .055 | -.561 | .005 |
| | | HMM | -.645** | .119 | .000 | -.942 | -.348 |
| | IMM | HMM | -.367* | .119 | .012 | -.664 | -.070 |
| **EF-monitoring** | LMM | IMM | -.348 | .148 | .071 | -.719 | .022 |
| | | HMM | -.438* | .155 | .023 | -.827 | -.049 |
| | IMM | HMM | -.090 | .155 | .919 | -.479 | .299 |
| **EF-WM** | LMM | IMM | -.332* | .108 | .012 | -.603 | -.061 |
| | | HMM | -.761** | .114 | .000 | -1.046 | -.476 |
| | IMM | HMM | -.428** | .114 | .002 | -.713 | -.144 |
| **T-EC** | LMM | IMM | .810** | .109 | .000 | .538 | 1.082 |
| | | HMM | .977** | .114 | .000 | .691 | 1.262 |
| | IMM | HMM | .167 | .114 | .391 | -.119 | .452 |
| **T-SUR** | LMM | IMM | -.552* | .209 | .036 | -1.074 | -.030 |
| | | HMM | -.082 | .219 | .976 | -.630 | .466 |
| | IMM | HMM | .470 | .219 | .112 | -.079 | 1.018 |
| **T-NA** | LMM | IMM | -.462** | .134 | .004 | -.797 | -.127 |
| | | HMM | -.824** | .140 | .000 | -1.175 | -.472 |
| | IMM | HMM | -.362* | .140 | .042 | -.713 | -.010 |
| **T-AFF** | LMM | IMM | -.165 | .202 | .805 | -.670 | .341 |
| | | HMM | .251 | .212 | .569 | -.280 | .781 |
| | IMM | HMM | .415 | .212 | .164 | -.116 | .946 |

*Note*. See variable abbreviations in Table 1 notes. *CI* = Confidence Intervals for Mean difference, * p < .05, ** p < .01.

For Temperament, all three groups differed from each other on Negative Affectivity (LMM < IMM < HMM). On Effortful Control, LMMs scored significantly higher than both IMMs and HMMs, while IMMs and HMMs did not differ significantly. For Surgency, IMMs scored significantly higher than LMMs but not significantly different from HMMs. LMMs and HMMs did not differ significantly. For Affiliativeness, the groups did not differ significantly.

## DISCUSSIONS

In this study we used a community detection approach to complex network analysis for the first time in media research to explore the temperamental and EF profiles of MMs in early adolescence. The analysis yielded three fairly well-delimited groups of participants, with profiles that present certain similarities and differences. This method offers certain advantages and disadvantages, that can be mitigated when used in conjunction with other established methods, as we will discuss below.

From a methodological perspective, the community detection approach we used allowed data to self-organize in patterns indicating temperamental and EF variations that co-occur with MM behavior without the need to constrain group structure or dimension weight a-priori. When using normative guidelines or convention-based criteria (e.g., Ophir et al., 2009; Shin et al., 2020), the resulting groups are often treated as being discreet, as if they are fundamentally different from one another and did not result from slicing a larger group at a certain cut-off point on one indicator. Community detection allows individuals to coagulate into groups based on multiple characteristics simultaneously and the differences between them are represented alongside the similarities. The calculated modularity score indicates how distinct the communities are. The links between individuals inside each community and between those in different communities indicate within and between community similarities. By analyzing these indicators, along with group scores on the variables of interest, one can perform a more nuanced analysis of the factors that might be relevant for group distinctiveness and those that are not.

When paired with quantitative methods that indicate the magnitude of the differences between groups, community detection might reveal how MM changes with temperament and EF difficulties. For example, self-reported inhibitory control problems increased significantly from LMM to IMM and remained similar from IMM to HMM. At the same time, both types of MM were similar between LMM and IMM but increased significantly between IMM and HMM.

Thus, it seems that the significant increases in inhibitory difficulties preceded relevant increases in MM behavior, potentially indicating that the former contributes to the latter. This progression might also be analyzed in the opposite direction. Inhibitory control still undergoes relevant development in early adolescence, which might translate into fewer self-reported difficulties, better abilities in controlling media-related signals or stimuli and, finally, lower MM levels. Thus, analyzing the synchronized and unsynchronized differences in individual traits and MM frequency across groups may help us understand their dynamics during important periods of change, such as adolescence, when both self-regulation abilities and media behavior are developing (Galvan, 2021). Given the exploratory nature of the present study, the type of analyses we performed and the small sample size, this interpretation remains speculative. However, such observations support the usefulness of complex network analysis and its community detection approach in capturing snapshots of such dynamics between media behavior and individual characteristics, as the person moves along these continue.

From a theoretical perspective, the differences and similarities we observed between LMMs and HMMs can also contribute to certain explanations of MM behavior. HMMs reported more time engaging in both types of MM, more frequent EF problems on all five domains, lower temperamental EC and higher NA than LMMs, who presented the opposite pattern of scores. These results tend to support the theoretical approach that paints HMMs not as strategic users, but as having difficulties monitoring and controlling media behavior and resisting interference from irrelevant stimuli or intense emotions (e.g., Ophir et al., 2009; Baumgartner et al., 2014). While it is probable that HMMs also engage in MM strategically, it seems more likely that a greater proportion of MM results from self-regulation lapses for HMMs than LMMs.

Last, the two types of MM occurred similarly frequently within each group. Our findings did not show that M-MM and A-MM co-occur with different combinations of temperament and EF difficulties, indicating that individuals who engage in MM more frequently tend to do so across context and regardless of activity combinations. Again, these results must be interpreted with caution.

Based on the group scores on temperamental Surgency (i.e., activity level) and Affiliation (i.e., sociability), we cannot speculate much about their possible relevance for MM behavior. First, Affiliativeness does not differ between the three groups, indicating that all adolescents have similar sociability needs and tendencies. This is likely a developmental characteristic that reflects the increased importance of socializing and creating meaningful relationships during adolescence (Lam et al., 2014). However, Surgency seems to be significantly higher in IMMs than LMMs, but no other differences have been observed. This difference may partly explain the somewhat higher frequency of M-MM in IMMs as opposed to LMMs. This aligns with findings in the literature linking greater sensation seeking with more frequent MM (Duff et al., 2014). However, given that the difference in MM between LMMs and IMMs is not significant, we must take this explanation with caution.

**Limitations and future directions**

Although the main objective of the current exploratory study was to demonstrate the usefulness of community detection complex networks analysis for studying media use, there are some relevant limitations that pertain to interpreting the results. First, the study is underpowered, given the limited number of participants and increased number of measures. More participants would increase the chance of more reliable findings. Secondly, while the analysis resulted in three adequately distinct groups, as indicated by the modularity score and by the following MANCOVA, MM and EF problem scores were moderate in the sample and extreme scores were infrequent. An increase in score range and variability on these measures might lead to a different network structure and number of communities. Thus, given the reduced sample size, the structure of the network and its communities must be taken as preliminary. Third, given that data was collected at a single point in time and the type of analyses we conducted, we cannot support causal inferences. While we did speculate on some potential associations between the variables that contributed to the three emerging groups, the analyses we carried out do not support causal interpretations. However, our results can constitute a base for further studies.

For example, we speculated that the patterns of changes between the three emergent groups might reflect a dynamic between dimensions of temperament or EFs and MM as the individual moves along them. This possibility might be investigated in a larger, longitudinal study, that follows the same individuals across adolescence and monitors how temperament, EFs and MM change and what their relationship is in various points of development.

We must also keep in mind that the dynamic between individual traits, behavior and other factors depends on context. They might interact differently depending on context affordances, which might translate into different observed relationships and co-occurrences. For example, it has been previously shown that good self-monitoring predicts increased A-MM but not increased M-MM (Rogobete et al., 2024). In this case, it is likely that the task at hand and the context surrounding it played a role in determining how important certain characteristics are for modulating MM behavior. It follows that the networks and profiles we observe in one context might be different from those observed in another. Further studies can aim to generate networks and explore communities in various (task) contexts.

Finally, complex networks analysis and community detection allow for multiple uses and might be combined with other types of methods, depending on the sample and the amount of available data. For example, they may be combined with qualitative methods that target the individual to extract more nuanced information about the characteristics of the emerging communities in the context of a limited sample.

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### Data availability statement

Data is available at the following link:
https://figshare.com/s/449e1bbd032919eeb44c
Data analysis script is available upon request to the first author.

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### Disclosure of interest

The present study is part of a PhD thesis, submitted and successfully defended by the first author in Cluj-Napoca, Romania. The first author assumed the responsibility of publishing all remaining results in the thesis after title attribution. The authors report there are no other competing interests to declare.

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