THE EFFECT OF NETWORK EMBEDDEDNESS: SOCIAL INFLUENCE AND LATENT SPACE POSITIONS ON TEACHERS' RESOURCE CURATION

By

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ABSTRACT

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Few studies on teachers' social networks have extended their scopes from schools to online, leaving gaps and the potential to study how school and district colleagues as well as online-only peers can exert a network influence on teachers' online resource curation activities. These studies have underused the relational-event social-influence model along with the latent space model to estimate the social influence process of teachers' online resource curation, while taking into account their latent positions for potential resource-mediated social selections. Also, few studies have defined the network embeddedness of teachers' resource curation regarding the direct social context of interpersonal networks, as well as the indirect context of the teacher-resource two-mode social space. This dissertation attempted to use the relational-event social-influence model to estimate the online network influence on teachers' resource curation activities, while accounting for a potential resource-mediated social selection process using the latent space model. Using a sample of 55 teachers from Waters School District in Indiana and their curation data on 81 resources across 48 weeks from 2016-17, I found a significant network exposure effect, specifically from online-only peers, after accounting for the potential resource-mediated social selection process. Several interaction effects of individual attributes and resource curation contexts have also been found to moderate the network exposure effect. In conclusion, teachers were influenced by their online networks when curating resources. Though both were significant, the resource-mediated social selection process was not confounded with the social

influence process in the one-mode interpersonal network, suggesting that the two social contexts teachers are embedded in played different roles in affecting teachers' resource curation.

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INTRODUCTION

Many studies in the fields of teacher networks and professional learning communities have found evidence of the importance and effectiveness of teachers relying on their network members as social capital and support for professional learning and development (Frank et al., 2004; Frank et al., 2011). Nevertheless, few studies have extended their network models from schools to online, leaving gaps and the potential for researchers to study how transcendent collegial relationships as well as purely online-established relationships can exert a network influence on teachers' educational resource curation activities—a process of teachers' seeking, sorting out, and saving resource content for professional purposes. This calls for actions to explore how teachers' diversified online networks would affect their resource curation.

Big data from social media provides educational researchers opportunities to study time-stamped teachers' curation of resources in combination with their social interactions online (Vu et al., 2015; Liu et al., 2020). Depending on the types of network data collected, researchers either rely on one-mode interpersonal networks (Frank, 1995) or two-mode social event participation networks (Doreian et al., 2004; Field et al., 2006) to capture the network embeddedness of individuals' activities. Nevertheless, teachers are often simultaneously embedded in these two types of networks, which jointly define teachers' network embeddedness in a social space. Hence, missing any layer of this double network embeddedness will render bias in making inferences on the network effects of teachers' resource curation.

Beyond the availability of big data, advancement in social network analysis presents researchers a spectrum of network models, each with different capacities. Some can model network peers' influence effects on teachers' curation activity (such as relational event models) (De Nooy, 2011; Liu et al., 2020), and others can model the selection effects of teachers' resource curation tie formation along with the network dependencies on the overall network structures (such as latent space models) (Hoff et al., 2002; Snijders et al., 2013; Fujimoto et al., 2018).

Nevertheless, the intricacy of teachers' resource curation activity adds complexity for researchers to choose the appropriate network statistical model. Previous studies either framed teachers' resource curation as an activity or relational event occurrence, subject to peer influence in their social contexts as well as other covariates such as time or within-teacher random effects (Liu et al., 2020). Teachers' resource curation can also be regarded as a two-mode network tie—teachers are indirectly connected to one another via participating in the same social learning event (i.e., curating the same resource in online spaces)—which is also subject to structural dependencies of the overall network in one's indirect social context. An incomplete view of teachers' resource curation can constrain network scientists' approach to specifying models to capture both peer influence and the impact of the overall two-mode teacher-resource network on teachers' resource curation.

Subsequently, the danger of ignoring the structural dependencies of teacher-resource network data can result in overestimating the peer influence effect (Xu, 2016). Thus, to address this issue, a model that incorporates both the exogenous social influence effect and the endogenous social selection effect would be needed to properly estimate how teachers' resource curation is influenced by that of their network peers.

Motivations of This Dissertation

Equipped with big data capacities and acknowledging the importance of peer influence on teachers' professional learning, it becomes critical to statistically test the salience of peer influence in the context of teachers' resource curation on social media, while also controlling for the teacher-resource network tie dependencies on the overall network structure. This dissertation attempts to use a latent space approach to estimate the latent positions of teachers and resources in the two-mode networks in an effort to account for tie dependencies on the overall network structure.

Furthermore, a relational event model will be used to estimate the social influence effect of network peers on teachers' resource curation while controlling for tie dependencies of teacher-resource networks using estimated latent positions. Such a model has the advantage of taking teachers' double network embeddedness into consideration, capturing a more complete picture of teachers' embeddedness in double-layered online social contexts—both their interpersonal networks and teacher-resource two-mode networks—and their subsequent impact on teachers' resource curation.

Teachers' Online Resource Seeking

Facing multiple challenges, teachers may seek resources and help from their collegial networks. Studies showed that collegial networks and teacher collaborations help reduce teacher burn-out (Russell et al., 1987), increase resilience (Frank et al., 2020), improve professional skills (Penuel et al., 2012), and make implemented school intervention more sustainable (Frank et al., 2011). In addition, support from network members is particularly crucial for teachers whose class composition includes mainly underrepresented students, as resources teachers have access to may not be adequate to meet the learning needs of students in these situations (Berebitsky & Salloum, 2017; Castro et al., 2010).

The professional networks through which teachers access resources are often constrained by formal organizational boundaries. On the positive end, the professional networks at school solidify internal connections, strengthen teaching norms, and create consistent teaching practices

(Bidwell & Yasumoto, 1999; Bryk & Schneider, 2002). Nevertheless, regular interactions with the same group of school-based colleagues expose teachers to redundant information (Burt, 2001), which poses an issue when teachers need novel teaching ideas and inspiration to tackle constantly changing scenarios in the classroom (Krackhardt et al., 2003).

Hence, it becomes crucial for teachers to connect to broader networks for new resources and knowledge. A typical way for teachers to make new connections, learn, and exchange ideas with one another is to attend professional development (Coburn & Russell, 2008). This relies on school and district leaders' efforts to create opportunities for professional interactions, encouraging teachers to connect and sustain those relationships (Frank et al., 2011; Horn et al., 2020). Altogether, these professional trainings and professional learning communities play an essential role in bridging educators to those outside of their school organization, connecting them with broader networks of teaching professionals (Penuel et al., 2018).

In recent years, social media has afforded teachers the opportunity to connect online with their school and district colleagues and with peers they may not be able to meet face-to-face. Digital platforms and social media deliberately encourage teachers to interact, express their opinion, and create and share educational resources they find useful (Greenhow & Galvin, 2020; Henderson et al., 2013; Pinterest Labs, 2022; Szeto et al., 2016). All of these have wide-ranging implications on teachers' engagement and interactions with peers in the teaching profession, as social media interactions are not bound by the organizational boundary of school, nor by geography (Torphy et al., 2020).

LITERATURE REVIEW

Overview of the Literature Review

In this section, I will first review how researchers draw on social capital and social learning theories to frame teachers' networking activity and its subsequent influence on teachers' professional learning efforts. This is to establish the empirical background for introducing literature surrounding the network influence model and the relational event model. Next, I will present literature on the co-existence of learning and socialization in online social spaces, in which I further evaluate studies that focus on the network structural implications of individuals' social learning activities. This is to set the stage for reviewing latent space models when capturing the social structure of teacher-resource networks as teachers curate resources via social media platforms. Furthermore, I will review various perspectives employed by current literature to investigate teachers' resource curation activity.

Starting from *Analyzing Teacher Resource Curation Two-Mode Network*, the second part of my literature review focuses on the network theories and methods surrounding social influence and selection processes in the context of two-mode networks. This is to provide a prelude to my research questions concerning resource curation in the framework of teacher-resource two-mode networks. Specifically, I conducted this literature review on how teachers' resource content curation can be impacted by the exogenous social influence process of their network peers' curation activity, as well as simultaneously subject to the endogenous resource-mediated social selection process. For instance, Ms. Jane would be influenced by resources curated by her online peer, Susan, to whom she is directly connected; in addition, Jane is also subject to resources curated by Bob, to whom she encountered during her visit to a resource space that she may or may not be directly connected with.

Thereafter, I introduce the relational event model with network exposures as the methodological approach to study the dynamic social influence process, followed by theories and methods (e.g., the latent space approach) to model the resource-mediated social selection process—tie formation in two-mode networks. Lastly, I reviewed and commented on the research potential and limitations of current methods for disentangling the social influence process from the social selection process, with an aim to investigate the social influence effect of teachers' resource curation while accounting for the endogenous resource-mediated social selection.

Social Capital Theory and Social Learning Theory

Research in social influence investigates the consequences of the network connections on one's behavioral changes (Friedkin & Johnson, 2011). Several sociological and social psychology theories are rooted in and have developed through the intersection of social networks and social influence. Among these theories, social capital theory (Lin, 2019) and social learning theory (Bandura & Walters, 1977) are widely applied in social sciences and the field of education.

Social Capital Theory

The research of social capital regards individuals as active agents, reaching out to socially-connected others for information or support, in which the acquired resources are called their social capital (Coleman, 1988; Portes, 1998). Social capital comes in a variety of forms, including information, opportunities, motivations, and abilities (Adler & Kwon, 2002), which are regarded as resources that can be mobilized via the network.

Empirical applications of social capital theory include job opportunities via personal contacts (Granovetter, 1973), financial transactional favors in a group of French bankers (Frank

& Yasumoto, 1998), and advice seeking among teachers at school (Frank et al., 2004; Penuel et al., 2009). Furthermore, two competing arguments in social capital theory, the effects of strong ties versus weak ties for acquiring information and support, were explored across different contexts (Friedkin, 1982; Liu et al., 2020). Studies indicated that strong ties improved the efficiency of social exchange due to mutual trust and group identification, lowering the transactional cost (Krackhardt, 2003), whereas weak ties promoted information dissemination based on diverse access to different sources (Bakshy et al., 2012; Ruef, 2002).

In terms of social capital in teacher networks, studies have found that educational resources (Liu et al., 2020), the ability to interpret accountability pressure and curricular standards (Frank et al., 2020), and expertise in computer technology (Frank et al., 2004) were able to be mobilized in the network to increase teachers' human capital. Teachers, as individual agents, also establish their networks outside of schools in online spaces, largely expanding the range of their social networks, in which social capital, such as educational resources, are accessed via online network connections (Kelly & Antonio, 2016; Torphy et al. 2020; Wesely, 2013). Thus, further investigation into the social capital embedded in individual teacher's online networks is needed, which has implications on teachers' professional learning and growth.

Social Learning Theory

Social learning theory describes a type of learning approach through observing others in one's social contexts, leveraging the social nature of human learning (Bandura & Walters, 1977). Behind this, social influence functions as the underlying process through which actors observe and are influenced by others' behavior (such as others' resource curation activity), learn from their social contexts, and change their behavior or level of knowledge as a reflection of their learning outcome (e.g., teachers' curation of a new resource). Insofar as some types of social exposures are present, direct interactions are not necessary for social learning to happen (Rogers, 2003).

In connecting social capital theory with social learning theory, social capital is a critical factor for the creation of human capital, in which the learning outcome is the human capital that has been developed by observing the activity of socially-connected others, with information and knowledge transmitted in the process (Adler & Kwon, 2002; Coleman, 1988). In fact, scholars have pointed to the direction of extending social learning research to incorporate a social network approach, increasing the analytical capacity of examining the social aspects of an individual's learning (Haythornthwaite & De Laat, 2010).

Social Learning within Professional Learning Spaces

Some literature that is closely related to social learning theory and teacher networks is about teachers' professional development and professional learning communities. Inside the professional learning community, one way for professional development to be promoted and sustained is to encourage discussions and collaborations among teachers (Coburn et al., 2012; Daly, 2010; Frank et al., 2011). Regarding the objective of teachers' professional learning, it ranges widely, including technological skills (Frank et al., 2004), mathematical knowledge for teaching (Sun et al., 2014), instructional practice (Penuel et al., 2009), and curriculum implementation (Coburn & Russell, 2008), all of which were better achieved under the mechanism of social learning. Studies have found similar results for teachers participating and collaborating in online professional learning communities, which benefited teachers' professional learning outcomes (El-Hani & Greca, 2013; Macià & García, 2016).

To conceptualize the professional learning space, various frameworks have been developed, each with slightly different emphases on the network components, collaborations, social exchanges, knowledge sharing, and learning. These efforts appeared as early as the Community of Practice in Lave and Wenger's (1991) Situated Learning Theory and flourished with frameworks like the Distributed Learning Community (Haythornthwaite, 2002), Knowledge Sharing Community of Practice (Ardichvili et al., 2003), Knowledge Building Community (Scardamalia & Bereiter, 2006), Networked Learning Community (Jackson & Temperley, 2007), Networked Improvement Community (Bryk et al., 2011), Socialized Knowledge Community (Hu et al., 2018), etc.

In conclusion, the information individuals acquire via interpersonal networks can be regarded as their social capital and the outcome of social learning. In summary, the above theories put into perspective the benefits and impacts of social interactions, which can be framed as the process of social influence to generate changes in individuals' knowledge and behavior.

From Physical to Virtual: Teacher Networks in Online Social Platforms

Teacher networks inside a school boundary are often studied in organizational research. Schools and districts are natural social systems, in which teachers frequently interact, collaborate, strive for common goals, and face similar challenges (Frank et al., 2020; Penuel et al., 2009). Organizational boundaries demarcate a holistic social system, which sets individuals within a system apart from the outside by norms, culture, contexts (Coleman, 1988), and resource possession and distribution (Santos & Eisenhardt, 2005).

Though each teacher's experience could be unique, larger environments such as district-level policy, school norms, and student background are strong drivers of teachers' resource-seeking patterns and teaching practices (Coburn & Russell, 2008; Torphy, Liu, et al., 2020). Within the natural boundary of schools and districts, a network of teachers evolves through regular interactions and relational expectations that colleagues would exchange ideas and share knowledge. All of these have an impact on resource flow, professional learning, and the implementation of new professional practices within a social system.

With the development of online platforms, virtual spaces that contain information about professional knowledge and social network functions began to gain teachers' attention and soon became self-organized social learning communities. These types of online communities fundamentally distinguished themselves from the professional learning community held by districts and states, in terms of the size (Kelly & Antonio, 2016; Macià & García, 2016), network structures (Karimi, 2020), teachers' initiative (Weseley, 2013) and flexibility in forms of collaboration (Seo & Han, 2013).

As teachers began to use social media for professional purposes, they also expanded the pool for collegial relationships to online platforms. Lying on a continuum of personal relationships across physical and virtual space (Wellman, 2004), teachers self-organize and preserve their interactional patterns with school colleagues on social media (Chen et al., 2017). Consequently, the organizational boundary is also projected into an online space (Torphy, Liu, et al., 2020). Results from a study of teachers' online interactional patterns on Pinterest indicated that teachers that were snowball sampled from a school district were densely connected, compared to teachers that were randomly sampled at the state level (Karimi, 2020).

Wellman (1999) argued that online networks are not only desirable for supporting weak ties but also for maintaining strong ties. In the context of teacher networks, research has found that teachers maintain their relationships with close colleagues at school, as well as other school-based and district-based colleagues on Pinterest, sustaining a spectrum of relationships in the physical space via the online platform (Liu et al., 2020). In addition, online interactions with existing colleagues on social network sites increase both the bonding and bridging social capital of individuals (Steinfield et al., 2009). In other words, online interactions simultaneously reinforce the existing relationships and expand one's capacity to access expertise embedded in a collegial network.

In an unbounded online space, teachers can express their networked individualism (Rainie & Wellman, 2012) and establish connections with peers encountered in the virtual space. In one study, teachers, on average, followed 150 individuals on Pinterest, among which approximately 97% were peers outside of their district boundaries (Liu et al., 2020). In a sense, teachers extensively expand their professional networks online, following individuals who are not in their original social circle for broader professional support and diverse sets of information.

As most ties are specialized, each providing support in a few dimensions (Wellman & Wortley, 1990), diversifying and connecting to a wider range of online peers—beyond school and district colleagues—provides teachers access to copious educational resources that are created and shared by individuals with dedicated strength and various perspectives (Frank & Torphy, 2019). In fact, Wellman (1999) discussed two types of networks, comparing the densely-knit tightly-bounded network with the sparsely-knit loosely-bounded network, in which he argued that the latter becomes a dominant form of interactions and collaborations in virtual communities.

The Co-existence of Learning and Socialization in Online Social Spaces

Unlike teachers' activities in physical spaces, online engagement greatly depends on the affordances of each social media platform. Various educational researchers have conceptualized each platform's affordances based on teachers' and students' online experiences, including personal profiling, content creation, authentic learning, information searching, resource sharing, relationship building, socializing, social participation, collaboration, community building, and evaluation and feedback (Greenhow & Galvin, 2020; Henderson et al., 2013; Szeto et al., 2016). It has been increasingly clear that the social participation feature in online platforms is essential to and inseparable from teachers' online professional learning activities. When online resources function as both a source of knowledge and a social event, learning and socialization co-exist in the online space (Hu et al., 2018).

Implications of Social Learning Activities on Social Structures

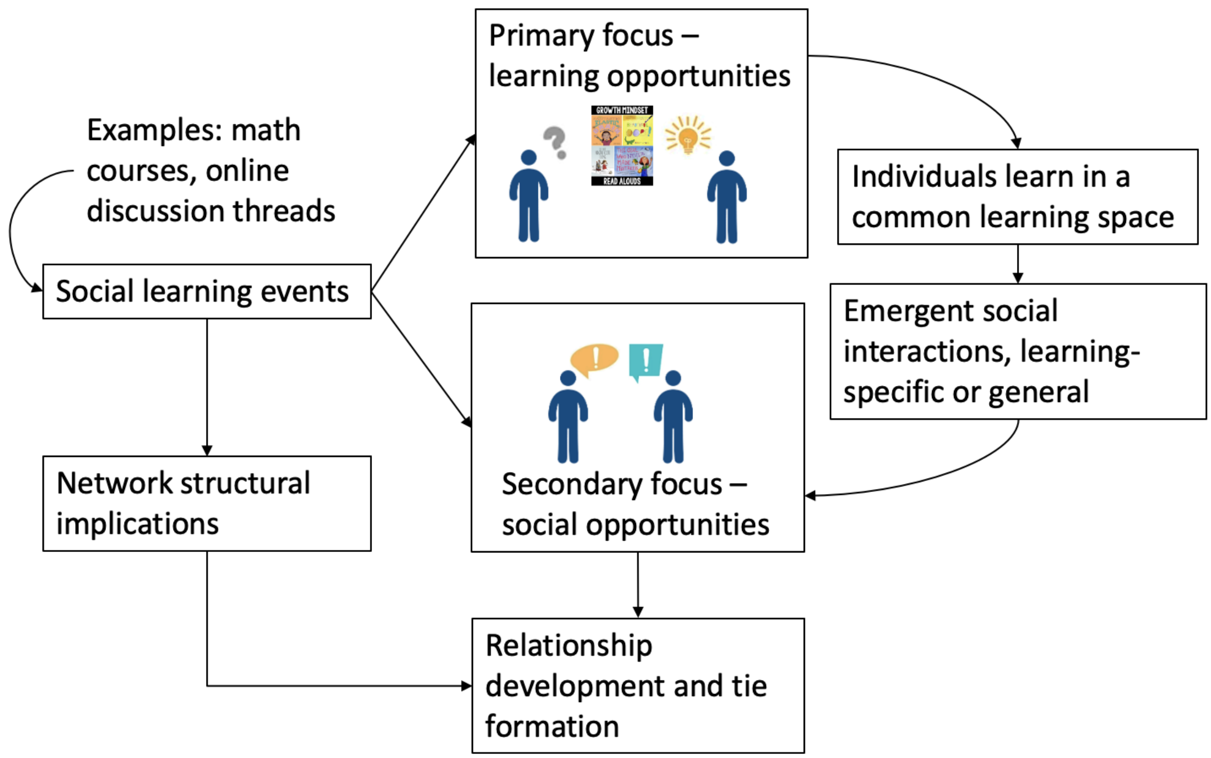
Previous research has investigated the patterns of actors' learning activities in a social space with respect to its implications on social structures. Using data on high school students' course-taking patterns, Frank et al. (2008) argued that adolescents' social contexts would be defined by those who took similar math courses, in which the aggregates of actors and courses jointly determined their local positions in a social space. In this study, math courses function as a primary learning opportunity and a subsequent social event through which individuals observe, conform to, and are influenced by decisions of peers in their local positions via common course participation.

Similarly, Vu et al. (2015) took a social structural approach to study online learners' contributions to discussion threads. Inside the online forum, learners can initiate a discussion thread to ask questions and receive responses and comments from other learners. Though mainly designed to leverage the learning assistance between learners in the online community, discussion threads contain the social network feature, which increases the likelihood of participants to further contribute to the same discussion thread.

These studies illustrate that a learning event is both a learning and a social event, be it a course, a discussion thread, or an online resource, creating opportunities for individuals to interact and develop relationships (See Figure 1). Subsequently, these social learning opportunities shape individuals' common participation in future learning events throughout the entire learning process.

Figure 1

Conceptualization of Learning and Social Elements of a Social Learning Event



Teachers' Resource Curation

Resource curation stems from digital content curation, which describes a series of information-seeking and management activities, including selecting, sorting out, annotating, archiving, and sharing of digital content (Flintoff et al., 2014; Yakel, 2007). With the increased use of social media, resource curation has gained attention as people curate content on social media platforms (Baruch & Gadot, 2021; Villi et al., 2012). In education, teachers' online activities of seeking educational resources and professional support are found to be a new form of professional learning and professional development (Carpenter et al., 2018; Greenhow et al., 2020; Manca & Ranieri, 2017; Trust et al., 2016). Previous research has employed several different perspectives to investigate the phenomenon of teachers' resource curation, concentrating on the curation activity, the resulting curated content, and the social process of the content curation (Cherrstrom & Boden, 2020).

Resource Curation as a Professional Learning Activity

Extant literature views teachers' resource curation through resource-seeking and learning activities, driven by individual professional needs and interests in the form of personalized and self-directed learning (Carpenter et al., 2018; Gadot & Levin, 2012; Greenhow et al., 2020). Factors like grade level taught, teaching dispositions, and school and district contexts are found to be predictors of teachers' common resource curation activities (Torphy, Liu, et al., 2020). Arguably, shared interests on specific content and the subsequent curation activity could also be due to some unobserved variables (Stephens et al., 2016), such as teaching styles and teachers' resource preferences.

Curated Content as Digital Assets and Tacit Knowledge

As to the result of teachers' resource curation activity, collections of curated content are considered as digital assets (Beagrie, 2008; Deschaine & Sharma, 2015; Yakel, 2007) and resource possessions of teachers (Liu et al., 2020). As curators often add a level of quality control and relevance during content curation (Flintoff et al., 2014), curated content is also viewed as a teacher's tacit knowledge, appearing to be an outcome of a teacher's professional learning efforts. In fact, scholars have attempted to analyze the quality of teachers' online lesson planning via assessing their curated content with respect to the dimensions of resource cognitive demand and depth of knowledge (Hu et al., 2021).

Resource Curation as Knowledge Distribution

Facilitated by the visibility feature of the social media platform, content curation approximates resource sharing and distribution, in which the curated resources are available to other curators in broader online communities through various paths, e.g., searching, direct visiting, following, and platform recommendations (Zhong et al., 2013). Curators are regarded as knowledge brokers, in which the sharing activity in essence is to distribute the content forward and provide access to others (Cherrstrom & Boden, 2020; Villi et al., 2012).

In the age of information excess, online resource curation, such as Open Educational Resources (OER), highlights its advantage on the collective efforts and network connections of trusted individuals who curate resources with some extent of quality control and are suitable under a given professional context (Bhaskar, 2016; Villi et al., 2012). Returning to Wellman's argument on networked individualism, teachers assemble their personal networks for content curation on social media based on their needs, in which they define their social contexts and accumulate the social capital of educational resources via online personal connections.

Analyzing Teacher Resource Curation Two-Mode Network

Teachers' online resource curation data belong to two-mode networks. A common approach to measure network structures of social interactions is via collecting one-mode network data—a single mode of teacher-to-teacher interactions or relationships. Yet, a different type of network data—two-mode network data (also known as affiliation networks or bipartite networks)—also has the capacity to capture teachers' social interactions through tracing their attendance and engagement in social learning events, in which teachers and social learning events are the two modes of nodes that are tied in the network. In other words, instead of gathering the direct social interactions, two-mode network data collect individuals' social activities or affiliations with the social learning events (Borgatti & Everett, 1997; Doreian et al., 2004). Though teachers are not directly connected with one another, social learning events mediate and play a bridging role to connect individuals who participate in the same events (Fujimoto et al., 2018).

Duality of Teachers and Social Learning Events in Two-Mode Networks

As illustrated by Simmel (1955), the duality of modern social life encompasses both the individuals and their social group affiliation, in which individuals join social events based on shared interests, such as teachers curating the same resources on the social media platform based on shared interests, increasing their likelihood of forming interpersonal relationships. At the same time, social learning events can be characterized and grouped by shared members. In short, through individuals' social event participation, a social structure of individuals can be implied as well as common characteristics of social events (Doreian et al., 2004; Field et al., 2006).

One-Mode Projection of Two-Mode Networks

The most classical method for interpreting implied social structures is to project the two-mode network into the one-mode network (Breiger, 1974), assuming teachers who participate in the same social event have interpersonal connections. The advantage of the projection method lies in its straightforward approach of converting and deriving social connections between teachers from their social event engagement.

Nevertheless, several concerns have been raised regarding the projection method, such as loss of information on the event size and multiple co-occurrences between the same pair during the projection (Latapy et al., 2008). These issues turn the two-mode network structure issues into one-mode network tie weighting issues (Neal, 2013; Newman, 2001). In addition, the projection method also has the tendency to over-represent the network density and the overall level of clustering (Opsahl, 2013).

Preserving the Duality of Two-Mode Networks

To address concerns in transforming two-mode into one-mode networks, several studies chose to preserve the duality of two-mode networks instead of removing the social events and reducing the data to one-mode networks. For example, Frank et al. (2013) took a meso-level approach, interpreting the two-mode network structure at the cluster level. Specifically, they define local positions from both actors' and events as densely connected individuals and events within a cluster (Field et al., 2006; Frank et al., 2008). Beyond that, statistical network models have also been developed to study the social selection process and tie formation theories behind two-mode network configurations, such as two-mode relational event models (De Nooy, 2011) or latent space models that can be applied to analyzing two-mode networks (Hoff et al., 2002; Krivitsky et al., 2020).

Social Influence and Social Selection

Social influence and selection are two social processes that have been studied by network scientists to explain the interrelationships between network structures and individual behaviors. The social influence process, on one hand, describes how an individual's behavior could be affected by the social network she is embedded in, e.g., how teachers' resource curation can be influenced by their network peers' in their social contexts (Liu et al., 2020). On the other hand, the social selection process investigates how individuals' attributes—such as latent positions of teachers and resources in the context of teacher-resource two-mode networks—and their similarities, along with network dependencies on existing ties, can affect tie formation between any pair of nodes (Frank et al., 2008; Frank et al., 2013; Snijders et al., 2013).

Social Influence

The social influence process allows us to conceptualize changes in individuals' behavior as a result of interactions with others in their social networks (Burt, 1987; Friedkin & Johnsen, 2011). For example, changes in teachers' resource curation activity can be conceptualized as a result of teachers interacting with and being influenced by others in their social context. Social influence depends on exposure, which occurs when individuals actively seek information based on perceived referent expertise (i.e., information-based social influence), or when individuals perceive a norm in a social group (i.e., norm-based social influence). Changes in behaviors or beliefs in these two scenarios are attributed to social influence theory (Guimond, 1997; Kaplan & Miller, 1987; Lord et al., 2001; Werner et al., 2008).

In particular, the network ties between individuals function as a path for information to be transmitted or norms to be exerted, carrying the influence from one to another (Marsden & Friedkin, 1993). In summary, social (or network) embeddedness describes how one's social surroundings can determine to whom and what information and resources one has access to, functioning as both an opportunity and a constraint (Coleman, 1988; Granovetter, 1973; Uzzi, 1996).

Social Selection

Topics in social selection investigate individuals' interactions and the subsequent network structures as explained by factors such as individuals' node-specific characteristics, homophily between two or more people's node-specific attributes, preferential attachment (being attracted to popular others), and network dependencies among two or more ties. For example, social selection research investigates how latent attributes of teachers and resources predict the formation of teachers' resource curation ties. To further elaborate, the explanatory factors cover a range of parameters at varying levels, including micro-level nodal parameters (Bjorklund & Daly, 2021; De Choudhury, 2011; Wehrli, 2008), such as teachers' tendency to actively curate resources in social space; dyadic attributes (Kossinets & Watts, 2009; McPherson et al., 2001; Spillane et al., 2012), such as the inherent similarity of values between teachers and resources; meso-level local structural parameters (Fujimoto et al., 2018; Robins et al., 2009), such as the clustering tendency among teachers and resources; and macro-level global structural parameters (Goodreau et al., 2009; Kadushin, 2012; Kossinet & Watts, 2006), such as teachers' resource curation network densities.

In other words, selecting with which social event an actor is affiliated can be determined by the attributes of the actors and the social events (Berardo, 2014), the consistency of inherent values between actors and social events (Frank et al., 2018; Newcomb, 1961), and the existing social ties that could potentially affect the formation of new social ties (Fujimoto et al., 2018; Snijders et al., 2013). Later in my dissertation, I will introduce the latent space approach, which relies on the estimation of latent positions of teachers and resources to account for a series of above-mentioned social selection mechanisms and network dependencies in teachers' resource curation two-mode networks.

Taken together, teachers' resource curation can be affected by network structures in two ways,

1) direct social influence from connected others in the local network,
2) social selection process and tie dependencies in broader network structures, in which the current social activity of teachers' resource curation is embedded.

Modeling the Social Influence Process

Egocentric Networks

Many studies have tested the effect of social influence via estimating the network exposure effect through the individual's egocentric network data (Frank et al., 2004; Frank et al., 2020; Reddy et al., 2021). To represent one's immediate local networks, the egocentric approach is used to capture interpersonal relationships that are centered at each sampled individual (the ego) and link to others (the alters) with whom the ego has direct connections (Granovetter, 1973). For instance, Liu et al. (2020) collected teachers' egocentric network data and estimated the social influence effect from network peers on teachers' resource curation.

Different from the sociocentric approach, which measures the connections of a whole network, the egocentric approach focuses only on the targeted individual's direct social context, to whom the actor is exposed and influenced by (Perry et al., 2018). Thus, egocentric networks are desirable for sampling one's direct networks and modeling the social influence effect, which also requires additional information on the ego's and alters' behaviors and beliefs (Frank et al., 2020; Liu et al., 2020).

Network Exposure Models

Network exposure models, also called network autocorrelation models, have been developed to estimate the social influence effect while controlling for an individual's prior behaviors or beliefs. Previous research on modeling social influences have proposed different weight matrices in creating the network exposure terms to reflect different influence hypotheses on the social processes, i.e., the degree to which individuals are influenced, such as in what way are teachers influenced by their online networks.

Several studies have conceptualized the network exposures as the mean level of the behaviors of the alters in an ego's local networks, normalizing the total exposures by an ego's network outdegree, e.g., teachers are influenced by the average level of curation activities of a certain resource in their direct social context (Fujimoto et al., 2011; Leenders, 2002; Marsden & Friedkin, 1993). These types of conceptualizations originate from research on population in a closed social space, such as social influence in the diffusion of innovation, in which all colleagues' decisions and behaviors, adopting or not, are cognitively weighted by the egos to infer the current innovation adoption stage in their social environment (Burt, 1987; Valente, 2005). Indeed, close communities often stress group identities, encouraging conformity to norms as the underlying mechanism for social influence. Thus, normative influence is measured as the mean level of alters' behaviors in one's local network (Coleman, 1988).

In contrast, studies with contexts in a vast open social space for information-seeking employ an unnormalized total network exposures approach, with the hypothesis that individuals absorb and learn in an accumulative fashion under informational influence (Liu et al., 2020). Specifically, as opposed to social norms that are subject to the consensus of a group of teachers (e.g., how teaching should be conducted in a classroom), teachers' level of knowledge on a specific subject can only increase monotonically as they are exposed to an incremental amount of subjected-related content (i.e., teachers are under informational influence). The underlying assumption is that each additional network exposure to the information source contributes and cumulates into a stronger social influence on individuals' level of knowledge and practices. In addition, emulation is another hypothesis for social influence to occur. Individuals in the workplace could be exposed to people they don't directly interact with but still adopt their behavior to emulate them for competitive reasons (Burt, 1987).

When social networks (such as personal networks on social media) function as an information channel, as opposed to a collective that emphasizes group identities and norms, network influence is less about individuals changing their behaviors to conform to expectations and norms, and is more about adopting certain behaviors as a result of having access to information and knowledge (Coleman, 1988). To summarize, the underlying mechanism of social influence determines how the network exposures are mathematically formulated, which depends on the salience of the norms in the social contexts and individuals' intentions for information-seeking.

Dynamic Social Influence Process in the Framework of the Relational Event Model

Event History Model

To study the social influence process (such as how teachers' resource curation is influenced by that of their network peers), longitudinal data are often required to distinguish behaviors at different time stages to make a causal statement on the network influence effect (Friedkin & Johnsen, 2011). Event history analysis is a type of analysis that incorporates and explicitly models the time dynamic of an occurrence of an event in a population in either a continuous or a discrete time frame (Singer & Willett, 2003).

In applying event history analysis to investigate the network influence effect, several studies in the area of diffusion of innovation have framed the network exposure as a time-varying covariate, changing along the time span (Strang & Tuma, 1993; Strang, 1996; Valente, 2005). As alters choose to adopt the innovation at different time points, the social contexts of egos have changed accordingly, which leads to the occurrence of an ego's adoption behavior.

Beyond the time-varying peer influence, event history models also have the capacity to record temporal evolutions of the dependent variable as a series of observations leading up to the final occurrence of an event (a change in states). This approach provides the potential to investigate the dynamic social influence process, along with the specification of network exposures as a time-varying covariate. As to my dissertation, instead of regarding innovation as the event of interest, I concentrate on the occurrence of educational resource curation across a group of teachers.

Relational Event Model

Following the event history model tradition, Butts (2008) tailored the hazard function and developed the relational event model (REM) to study the temporal dynamics of social network tie occurrence. In the relational event model, network ties are framed as the relational events. When a network tie between a teacher and a resource is established, a relational event occurs, and the state of a teacher-resource-curation tie changes. That is, the relational event tie is the hazard, and its occurrence or not and *when* is what we estimate.

Specifically, the hazard function models a tie occurrence (i.e., a tie formation) at a certain time, which is conditional on the non-occurrence of that tie across all previous time episodes since the beginning of a study (De Nooy, 2011). In addition, depending on mechanisms of the tie formation, a relational event can also be modeled with covariates like time and network-specific parameters (such as individuals' tendency to form a tie or latent space positions of each node) in an ongoing dynamic fashion.

Relational Event Model in Studying Tie Occurrence in Two-Mode Networks

De Nooy (2011) extended the relational event model to the two-mode network scheme, studying book reviewers' selection of an author's new book with respect to time, author's node attributes, conformity of reviewers to authors (a tie-specific predictor), and other network parameters, such as two-path indirect connections. He further elaborated that snowball sampling of the surrounding network environment across temporal and social dimensions would be needed given the relational event model is actor-based and local in nature.

Thereafter, several studies have applied the relational event model to two-mode networks in the context of contributions to open-source software projects (Quintane et al., 2014), social learning in Massive Open Online Courses (MOOC) (Vu et al., 2015), favors in congressional collaborations (Brandenberger, 2018), and directors' and firms' board-interlock networks (Valeeva et al., 2020). Recognizing the tie dependency of existing relational events in two-mode networks, these studies took advantage of the time-ordered network data, testing hypotheses on various interaction-related tie formation mechanisms. Concretely, they followed the parameterization in the exponential random graph models (ERGM) tradition but leveraged the longitudinal capacity of the data, specifying network parameters that reflected the tie dependencies on both past as well as current relational events.

Limitations of Current Two-Mode Relational Event Studies

None of the two-mode relational event models described above incorporated the social influence process from one-mode networks into their frameworks. Yet, a recent study investigated teachers' resource curation of resources on Pinterest, in which exposures to colleagues' resource-seeking from one-mode networks were hypothesized as an explanatory factor and tested significant for the occurrence of relational events in two-mode networks—the occurrence of teachers' curating a resource (Liu et al., 2020).

In the study conducted by Liu et al. (2020), teachers' resource curation was modeled as a two-mode relational event, in which a teacher's hazard rate of resource curation was increased as more of her colleagues in the direct social surroundings began to curate the same resource. In a modified variation of their relational event outcome (frequencies of teachers' resource curation), results indicated that each network exposure to colleagues who curated a resource increased a teacher's frequency of resource curation by 1.67 times. This was the first study that attempted to statistically test the social influence effect on the two-mode relational events of teachers' resource curation by using one-mode networks and longitudinal observations to capture a constantly-evolving peer influence in teachers' social contexts.

The above two-mode relational event study did not address global network structural dependencies. As Valeeva et al. (2020) pointed out, a potential limitation of the relational event model is that it cannot capture the dependencies of a local network tie on other ties further away in the network, as actors may also respond to and coordinate with the networking activities of others outside of their local neighborhood. Thus, parameters that can capture the network dependencies among two-mode relational events are needed such that the social influence effect of teachers' resource curation can be estimated holding constant the social selection effect. Xu and Frank (2020) have also developed a simulation-based sensitivity analysis to test the robustness of social influence effects against six forms of social selection mechanisms, such as homophily and transitivity, which could potentially confound with the influence effect. Specifically, they attempted to address the question of how network exposure effects might change if people select and establish ties based on different mechanisms.

Modeling Social Selection Process Using Latent Space Models

Beyond the development of network models for testing social influence effects on individuals' behavior, a variety of statistical models have also emerged for tie formation and network structures of the social selection process. For instance, ERGMs deliberately specify each of the possible network configurations that are aligned with the social selection process in order to meet the partial dyadic dependence assumption (Robins et al., 2007; Snijders et al., 2006).

Nevertheless, Hoff et al. (2002) pointed out that model degeneracy and instability problems are less due to the estimation techniques, but more to the defects in models focusing on the global rather than local structures. They subsequently proposed latent space models as a solution.

Latent space models (LSM, also called latent position models) view the probability of a tie as some function of a pair of individuals' positions in a latent social space, in which the latent space positions represent individuals' unobserved characteristics. Two distinct features of LSMs unfold as follows: First, LSMs built upon the concept of social space, adapted from geographical space to the space of social interactions, which uses the geometric distance between individuals to represent social dependence (Carrington et al., 2005). Social positions, in a similar fashion, are "evidenced in the social interactions of individuals as occupants of positions and performers of roles" (Faust, 1988).

Second, the specific type of social space described in LSMs refers to "a space of unobserved latent characteristics that represents potential transitive tendencies in network relations" (Hoff et al., 2002). Using nodal latent positions (as a measure of unobserved characteristics) and dyadic distance or similarity between two individuals, the authors demonstrate the capacity to model the social processes under the premise that social ties are transitive in nature. In a sense, this method relies on the nodal and dyadic local structures as the building blocks and fundamental social dynamics for explaining and generating higher-order network configurations. See also Clarifying Terminology in Latent Space Model Literature under the Analytical Strategy section.

To elaborate on the LSM logic, if node *i* and *j* have a tie, this implies that *j* and *i* are also close in the latent space, which captures the tendency for a reciprocal tie at the dyadic level. At the triadic level, if node *i* and *j* have a tie, as well as *j* and *k*, then *i* and *k* are not far away in the latent space, thereby capturing the tendency for a triadic closure. In fact, Hoff et al. (2018) showed that the latent space approach effectively captures reciprocity and transitivity in cross-sectional network structures.

Compared with ERGMs, LSMs use a model-based graphical representation of network relationship and social positions in a lower dimensional space, with an emphasis on an additional assumption of the transitive nature of ties in the social space. Extending the LSMs' logic, LSMs can be generalized to scenarios other than transitivity that also satisfy this graphic configuration, such as structural equivalence (Faust, 1988). Therefore, networks that can be represented by the social processes of transitivity (structural influence) or structural equivalence (structural homophily), such as women social event participation of two-mode networks (Davis et al., 1941), are good contexts for using LSMs to account for the endogenous network selection process and network dependency in two-mode networks. Applying LSMs in the two-mode networks of teachers' resource curation would account for the endogenous social selection processes, such as the observed four-cycle network configuration, of which two teachers and two resources are connected and structurally dependent on one another.

Disentangling Influence from Selection in the Two-Mode Network

In research cited in previous sections, social influence and selection were not fully separated in modeling the relationship between individual behaviors and network structures. For example, although structural homophily (also called structural equivalence)—a social selection process—is commonly drawn on to explain a tie formation where two individuals of similar network positions tend to form a relationship, it has been investigated as a social influence process in innovation adoption literature. Burt (1987) found that individuals followed those who occupied a similar network position and subsequently conformed their behavior. In fact, this result captured a two-step social process—both selection and influence—such that the two are confounded with one another. Specifically, structural similarity generated some sense of relevance and indirect connectivity between two individuals. This type of connectivity further leads to social influence. In the scenario of teachers' resource curation, the two-step social process would be that teachers' connections via common visits to resource spaces represent social selection, which provides opportunities for subsequent social influence on teachers' curating activity.

Relatively recent studies have attempted to distinguish social influence from the social selection process (Fujimoto et al., 2018; Snijders et al., 2013), unfolding the complex chicken-and-egg problem by using structural homophily to explain tie formation in the presence of other existing ties, while partialling out the social influence effect. These studies also presented the multi-faceted nature of social event engagement behavior. That is, engaging in social events represents one's social networks and behaviors, which is subject to network dependencies in the process of social selection, and is malleable to change in the process of social influence.

Specifically, these studies have investigated the dynamics of one-mode and two-mode networks using the stochastic actor-oriented model (SAOM) (Fujimoto et al., 2018; Lomi & Stadtfeld, 2014; Snijders et al., 2013). With data on the co-evolution of one-mode and two-mode networks, Snijders et al. (2013) investigated the change of one's employment preference as both a function of the exogenous effect of social influence from the advice network and the endogenous selection effect of structural dependencies inside the employment preference two-mode network. Using a parameter of between-network mixed triad, Snijders et al. (2013) found that the advice ties of one-mode networks lead to agreements among students regarding their employment preferences in two-mode networks, in which the between-network mixed triad is composed of an advice tie (from one-mode networks) and two student-company preference ties (from two-mode networks).

Similarly, Fujimoto et al. (2018) found that adolescent friendship (measured in fall 2010) led to common participation in sports activities (in spring 2011), interpreting the impact of one-mode networks on two-mode networks as social influence effects, also called “friendship-based context assimilation.” In their context, the process of social influence is found to be stronger than that of social selection. In other words, the process of “friendship leading to common sports participation” was more salient than the process of “common sports participation leading to friendship formation.”

Furthermore, the authors were one of the first to use mixed triadic effects (i.e., a multivariate network term of transitive closure that integrates a single interpersonal tie with two social event affiliation ties) to parameterize the exogenous social influence effect (i.e., the effect of the one-mode on the two-mode network), while accounting for the endogenous social selection effect in two-mode networks (i.e., higher-order network configurations like the four-cycle parameter).

Limitations of Using Mixed Triads to Estimate Social Influence Effects

Compared with the two-mode relational event model used in Liu et al. (2020), the SAOM between-network-mixed-triadic-effect approach has several limitations. First, it does not specify the social influence process as a continuous time-varying covariate, in which the social influence of network peers cumulates in a time-dynamic fashion, and the estimation of the associated parameter leverages observations across multiple time periods in predicting changes in the hazard rate of teachers’ resource curation attributed to the social influence effect.

Second, using between-network-mixed-triad to approximate social influence assumes that influence would happen invariantly between any connected individuals as long as they have a shared sports activity (see Figure 2, the reproduced Figure from Snijders et al., 2013). This is due to the fact that the between-network-mixed-triad regards social influence as a network structural parameter, and not as a weighted combination between friendship network structures and friends' prior level of behavior. In a sense, the multivariate mixed triad approach fails to explicitly model the social influence using network exposure terms, which would be a multiplication of both the one-mode network ties and alters' prior behaviors.

Figure 2

Reproduced Figure from Snijders et al. (2013)

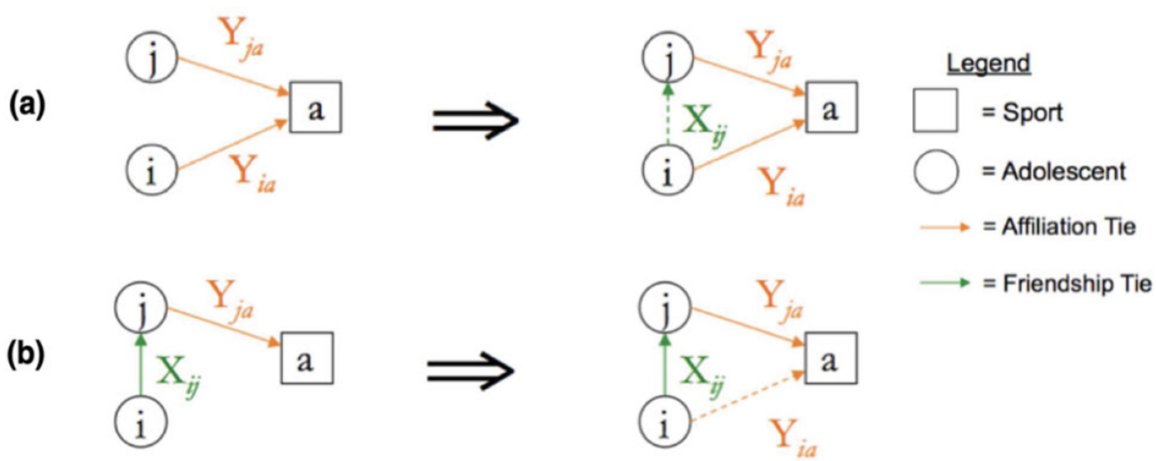


Fig. 1. Illustration of social mechanism of (a) "shared sports activities leading to friendship" and (b) "friendship leading to shared sports activities." Solid lines represent existing ties, and dotted lines represent formed ties.

Third, as Snijders et al. (2013) pointed out, it would be challenging to distinguish empirically whether the ego influenced the alter, or vice versa on the common participation of the two-mode social events using SAOM's between-network mixed triad.

Fourth, the SAOM does not model the social influence process with respect to each specific social event choice or preference that has been passed via network connections. In fact, Snijders et al. (2013) and Fujimoto et al. (2018) selected the most common social engagement activities in regard to their study contexts, i.e., employment preference among college students and sports participation among adolescents, which are social activities that would most likely be affected by advice-seeking relationships and friendships respectively. However, this approach would not be appropriate for contexts with diverse social engagement opportunities, of which each was determined by different social influence processes.

Lastly, the SAOM adapts the ERGM approach for accounting for network dependency, which could inherit the problem of model degeneracies and estimation difficulties. Therefore, an extension of the two-mode relational event model, with approaches to control for the endogenous social selection process (i.e. latent space model), would be needed to estimate the time-dynamic social influence effect of teachers' resource curation, while taking into consideration the latent positions of teachers and resources to account for network dependencies on the existing global structures of two-mode teacher-resource networks.

DISSERTATION SIGNIFICANCE: INTEGRATING THE RELATIONAL EVENT MODEL WITH THE LATENT SPACE MODEL

A Focus on Local Structural Parameters

Careful thoughts are given to network models that concentrate on local structures in comparison to global network structures. In fact, De Nooy (2015) provided his perspective on why he shifted the focus from global to local network structural parameters. In his view, "the overall network structure of interactions is merely a by-product of how social actors respond to their local network context" (p. 2).

De Nooy (2015) argued that the relational event model provided a straightforward framework for modeling the dynamics of local ties as a function of different types of social processes, e.g., reciprocation and triadic balance in time-varying interaction contexts, of which each can be formulated as independent variables in a regression analysis. As a framework for longitudinal network data analysis, the REM displays its advantage compared to the cross-sectional counterparts of ERGM.

Hoff et al. (2002) had similar concerns in modeling a variety of network parameters representing the overall network structures. Instead, they took a local structure approach by controlling for the latent positions of nodes in a social space. That is, the LSM approach decomposes the entire network sociomatrix to account for network dependencies by estimating specific parameters at the nodal level, instead of including complex higher-order network parameters (i.e., configurations with at least three network ties). Because LSMs are developed for analyzing cross-sectional network data, this approach attempts to model the tie formation at a local level using the nodal latent positions to account for a diversity of social selection processes, such as reciprocity and transitivity (Hoff et al., 2018).

The advantage of the LSM lies in its emphasis on how local ties function as building blocks—with tendencies of grouping and clustering for potential subgroup creation—which generate emergent overall network structures. This logic also leads to simplified network models with one term of (dis)similarity between latent positions of nodes at the dyadic level, without estimating each network configuration for all possible social selection mechanisms. In summary, the view of modeling two-mode network data through local network parameters is congruent between Hoff et al. (2002) and De Nooy (2015), both acknowledging and making connections between local network parameters and its contribution to or dependency on the final configuration of the entire network structure.

Combining Two Approaches

In my dissertation, I propose to combine a relational event model with a latent space approach in modeling teachers' resource curation in the framework of teacher-resource two-mode networks. Specifically, the LSM offers the flexibility to reduce a variety of social selection processes in teachers' engagement with social learning events to a similarity measure between the latent space positions of teachers and resources. Subsequently, the REM with estimated latent positions will further allow me to model the exogenous social influence effect, while also accounting for the endogenous selection effect. In connecting two approaches, we are empowered to leverage both the temporal dynamic capacity of modeling social influence in the two-mode relational event setting, along with a simplified approach to account for network dependencies of local ties on their global network structure.

CONCEPTUAL FRAMEWORK

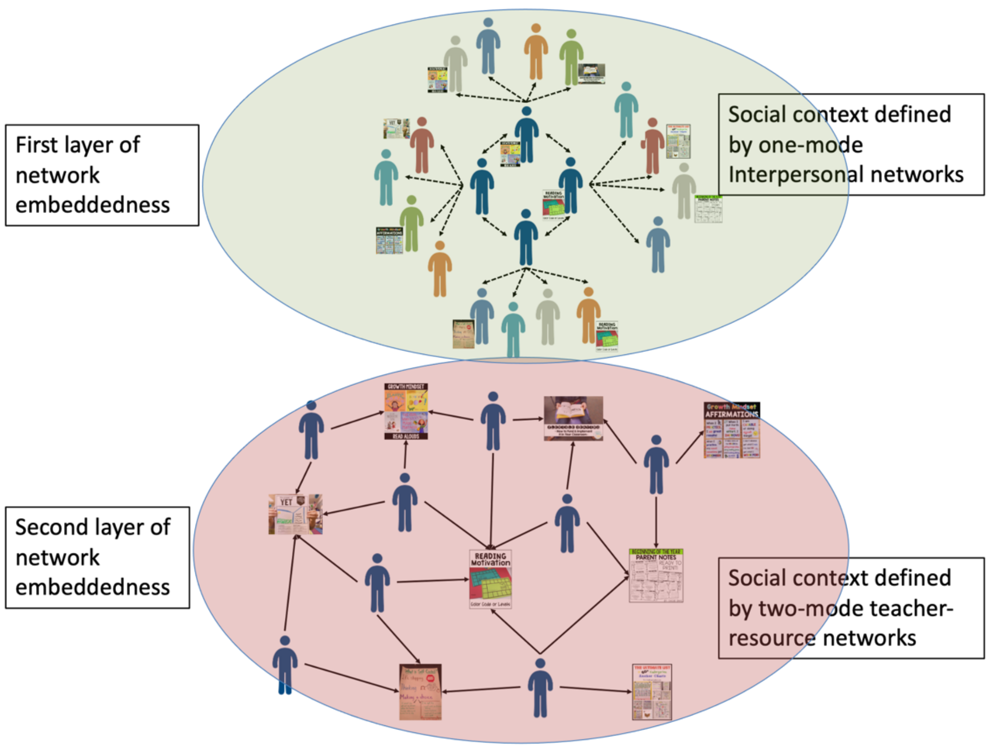
This dissertation focuses on investigating the social dynamics of teachers' online resource curation, particularly the social influence process of network peers' curation activity while acknowledging the resource-mediated social selection process during teachers' engagement with online resources in a social space. Previous studies have situated teachers' resource curation under the bigger theme of teachers' use of social media, in which social media functions as a technology tool and an online platform for teachers to continue their professional practices of resource seeking, lesson planning, social interactions, community building, and classroom teaching (Carpenter et al., 2018; Hu et al., 2021; Manca & Ranieri, 2017; Trust et al., 2016). In contrast, this dissertation concentrates on the network embeddedness of teachers' resource curation. Specifically, I conceptualize teachers' resource curation as teachers' professional learning activity, impacted by online peers' curation activity in their immediate interpersonal networks, as well as teachers' participation in a social learning event—a type of social engagement that increases teachers' likelihood of interactions, impacted by teachers' latent space positions in a holistic teacher-resource two-mode network.

Double Network Embeddedness

In a sense, teachers experience double network embeddedness in an online social space (see Figure 3), which simultaneously affords teachers the opportunity to build personal connections and conduct the social activity of resource curation (see Figure 4). The first layer of network embeddedness exists in teachers' direct interpersonal social contexts, in which teachers are exposed to resources curated by their network peers in the one-mode network. Furthermore, the social activities of teachers' resource curation define the second layer of network embeddedness, in which online resources play the role of social learning events, connecting teachers who curate the same resource. In other words, teachers are embedded in a social context co-determined by teachers and resources, while teachers themselves are indirectly connected to each other. The two-mode social space captures teachers' latent space positions and resources that flow in teachers' online neighborhoods, which further impacts what resources teachers may curate in the online space.

Figure 3

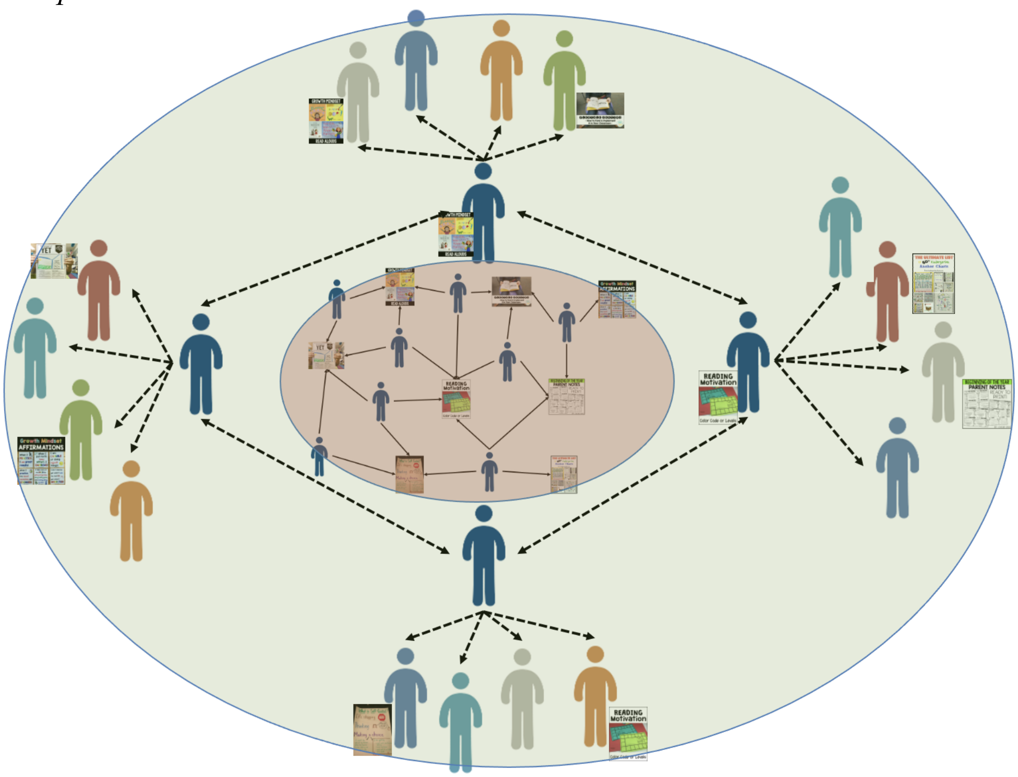
Double Network Embeddedness of Teachers' Resource Curation



Note. The upper social space is defined by one-mode interpersonal networks, in which teachers are embedded and curate resources as a consequence of the direct social influence from their network peers. The lower social space is defined by two-mode teacher-resource networks, in which teachers are embedded and curate resources as a result of their latent space positions in a broader network environment. Dashed lines represent one-mode network ties of interpersonal connections between individuals. Solid lines represent two-mode network ties of teachers' resource curation.

Figure 4

Teachers' Concurrent Embeddedness in Two-Mode Teacher-Resource Networks and One-Mode Interpersonal Networks



Note. This figure integrates two layers of network embeddedness from Figure 3 into one holistic frame to display the full scope of teachers' embeddedness in a social space, which allows teachers to interact with both people and resources at the same time. The inner circle displays teachers' resource curation as embedded in a two-mode teacher-resource network. The outer circle displays teachers' curation as influenced by and embedded in a one-mode interpersonal network.

In Figure 3, I separately presented the two layers of network embeddedness of teachers and their resource curation activity, highlighting opportunities and constraints brought by each type of network. In fact, when teachers are allowed to interact concurrently with other individuals and resources on a social media platform, both layers of network embeddedness occur at the same time. This means teachers' resource curation is subject to network peers' social influence in one-mode networks and their local network positions in two-mode networks in an inseparable fashion. Thus, I integrate the two layers of teachers' network embeddedness in

Figure 4 to show teachers' concurrent embeddedness in two types of networks in their social curation process.

Latent Space Positions in Two-Mode Networks as an Outcome of Complex Mechanisms

Latent space positions of teachers and resources in two-mode networks could be an outcome of both the selection and the influence mechanism. First, due to cognitive consistency, homophily, and structural equivalence, teachers of a kind select similar resources, reinforcing their positions in the latent space based on personal preferences and orientations, i.e., their unobserved latent attributes.

Second, seeing what resources colleagues curate is equivalent to knowing their personal preferences and professional orientation. Teachers are more likely to be influenced by individuals who are aligned with their professional views, thereby more likely to select resources curated by them. In short, the latent space positions of teachers and resources carry various types of information on whether and why teachers would select certain resources, observed as the realization of the two-mode network structures.

Bounded District Networks in an Unbounded Online Space

Mixed findings exist on whether teachers collaborate with colleagues from schools and districts within online social media. Some indicate that teachers' online activities on social media platforms, such as Pinterest, are mainly individual actions with few communications and collaboration, while others suggest that teachers collaborate online with other educators both within their district and around the world (Carpenter et al., 2018; Greenhow et al., 2020). I argue that school districts maintain their social salience even when teachers extend their professional relationships to the online space. In other words, teachers are embedded in a network of school and district colleagues in the online space, in which they keep track of and are influenced by their colleagues' resource curation activity.

In combination with the framework of double network embeddedness, teachers' curation activities are affected by the direct network influence from the one-mode online networks, as well as their latent space positions and nearby resources in two-mode teacher-resource curation networks. As district organizational boundaries are projected online, teachers from the same district are viewed as actors in a bounded district network in an unbounded online space.

Conceptualizations of Online Resources in Social Media Platforms

This dissertation leverages three conceptual understandings of the resources and operations in teacher resource curation networks. First, curated resources include tacit knowledge that are exchanged between individuals. In this view, resource curation amounts to teachers' professional learning activities. Subsequently, the cumulation of curated resources equals the increase in teachers' tacit knowledge.

Second, resources are conceptualized as social learning events, from which social structures emerge. Curating the same resource on the online platform increases teachers' likelihood of interactions in the resource curation space, which would further enhance their professional relationships.

Third, the curated resources are viewed as observations of teachers' latent attributes, reflecting their preferences and professional orientations. Teachers with similar latent attributes may curate resources alike, naturally drawn close to similar others and preferred resources in the two-mode teacher-resource social space.

The Standing of This Dissertation

Previously, Liu et al. (2020) investigated how teachers were influenced by their school and district colleagues' resource curation activity on social media. Using a sample of teachers who expanded their professional relationships from physical to virtual space, the authors tested the direct collegial influence in the online space. Specifically, they focused on the online collegial network influence of the blue actors in the upper social space in Figure 3. Nevertheless, their study only investigated the interpersonal network embeddedness (i.e., the first layer in Figure 3) and overlooked the social dynamics and impact of the two-mode teacher-resource networks (i.e., the second layer in Figure 3), which could confound with the network influence from the one-mode network.

Building upon Liu et al.'s (2020) framework, this dissertation attempts to study teachers' resource curation as they are embedded in both one-mode interpersonal networks and two-mode teacher-resource networks. Furthermore, this dissertation will expand the scope of teachers' ego-centric interpersonal networks by including both school and district colleagues (i.e., core blue actors in Figure 3), and online peers (i.e., peripheral actors in Figure 3), testing the overall network exposure effects on teachers' resource curation.

Altogether, teachers' resource curation is impacted by all network members' curation activity in their online interpersonal networks, both from colleagues in their school district and online-based peers (i.e., the first layer of network embeddedness in Figure 3). Furthermore, teachers' resource curation is impacted by their latent space positions in a two-mode teacher-resource network, in which the online two-mode network boundary includes teachers from the same district, considering its social salience (i.e., the second layer of network embeddedness in Figure 3).

Hypotheses

To test the social influence effect, I developed the two hypotheses below. Hypothesis 1 directly tests the peer influence effect on teachers' resource curation, while hypothesis 2 tests the same social influence effect while taking into account the resource-mediated social selection process during teachers' resource curation in teacher-resource two-mode social space.

Hypothesis 1—Teachers' resource curation is influenced by the direct network exposure to online peers in egocentric one-mode networks.

Hypothesis 2—The social influence effect of teachers' resource curation remains significant after taking into account the resource-mediated social selection effect in the teacher-resource two-mode social space.

Hypothesis 3—Teachers' online resource curation is influenced more by online-only peers compared to the network influence from their school and district colleagues.

METHODS

In this section, I will introduce the study context, the data source, the sample, the variables, and the analytical strategy used to test my hypotheses. In particular, the study context section will introduce where the empirical study settings were situated, specifically the characteristics of the Pinterest social media platform. Next, the data section will describe what types of network connection, resource curation and individual attributes data were collected and when they were collected. Furthermore, the sample section will introduce who were sampled and how they were sampled, including both a sample of teachers and a collection of resources. Finally, the analytical strategy section will introduce the statistical models employed to estimate and test the hypotheses.

Study Context

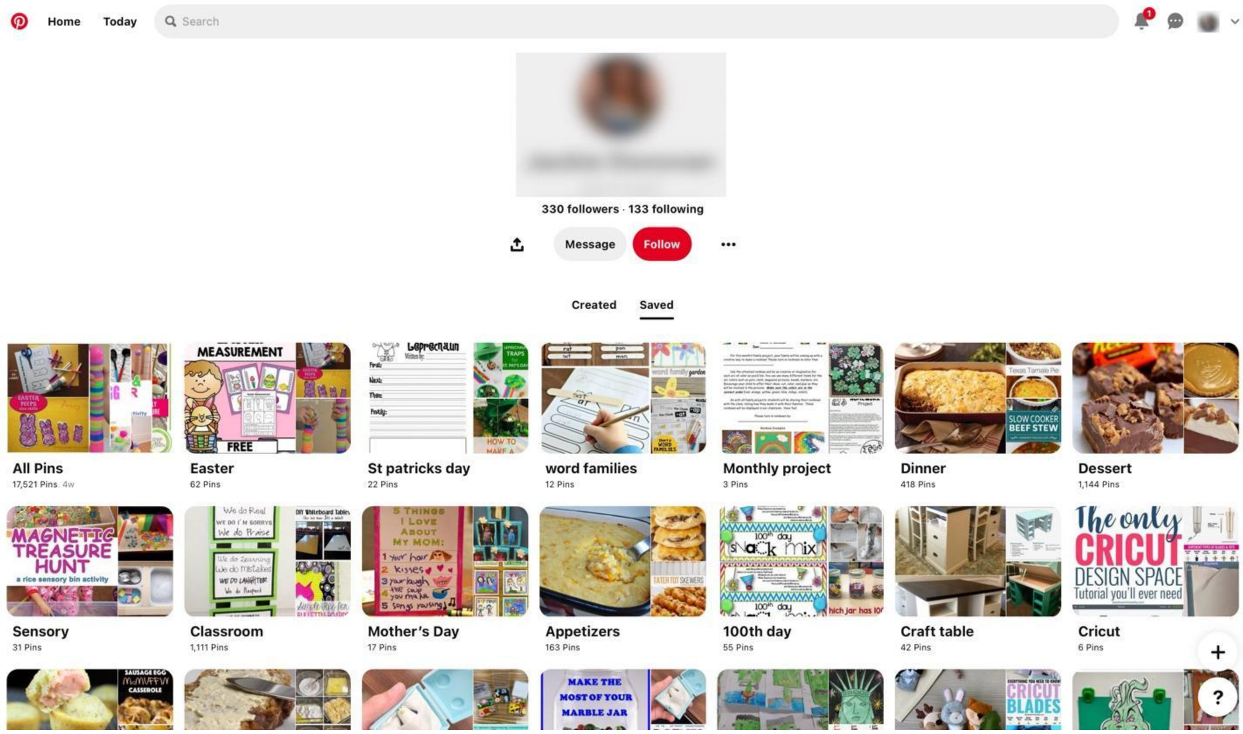
This dissertation is situated around Pinterest, a visual discovery engine and an image-based social media platform, which allows users to create, search, and save image-based content onto their user-defined boards. On Pinterest, image-based resources are called “pins,” and users who conduct the pinning activities are called “pinners.” Based on its platform statistics, Pinterest has 444 million monthly average users and 330 billion pins. Pinning activities on Pinterest describe individuals’ behavior of saving and curating image-based content onto their boards in a way that makes sense to them. Thus, I will use pins and resources, as well as pinning, saving and curating interchangeably in this dissertation.

According to descriptions from Pinterest’s website (2022), pinners use Pinterest mainly for idea inspiration, in which they look for a wide range of ideas, including food and drink, beauty, home décor, and more. Though Pinterest was not originally created for searching and sharing education-related resources, a study of elementary school teachers’ use of social media gathered data on their actual collection of resources, indicating that 77% of the sampled 90 teachers used Pinterest at least once a month for professional purposes (Hu et al., 2018). As a social media platform, Pinterest affords teachers the opportunity to follow one another, visit each other's homepage, and track resources that have been pinned by others beyond the teachers' own resource curation activities. Thus, Pinterest provides a natural setting for social network scientists and educational researchers to study the social network effect on teachers' resource curation.

Figure 5 displays an example of a Waters District teacher's Pinterest homepage. This teacher has followed 133 online peers and has been followed by 330 individuals, which formed her online personal network on Pinterest. The bottom of the page displays the resources pinned by this teacher, which have been sorted into boards under different themes. For instance, boards such as "Easter," "word families," "Monthly project," "Classroom," and "100th day" contained varying numbers of educational pins this teacher has found useful and saved for later use for teaching-related activities.

Figure 5

An Example of a Teacher's Pinterest Homepage



Pins - Resource Content and Social Spaces

According to Pinterest (2022), a "curated pin" is a bookmark of loved content people saved to their personal boards. Moreover, not only is a pin a content or resource, Pinterest also assigns each pin its own webpage, in which the comments section allows individuals to comment, reply, and like a pin, covering a variety of social engagement activities. Thus, each curated pin can be viewed as an online social space, in which teachers can interact, exchange ideas, and build relationships. Altogether, pins function as online social learning events, in which teachers can acquire knowledge as a way of professional learning through their pinning activities and interact with others by visiting and engaging within the resource space.

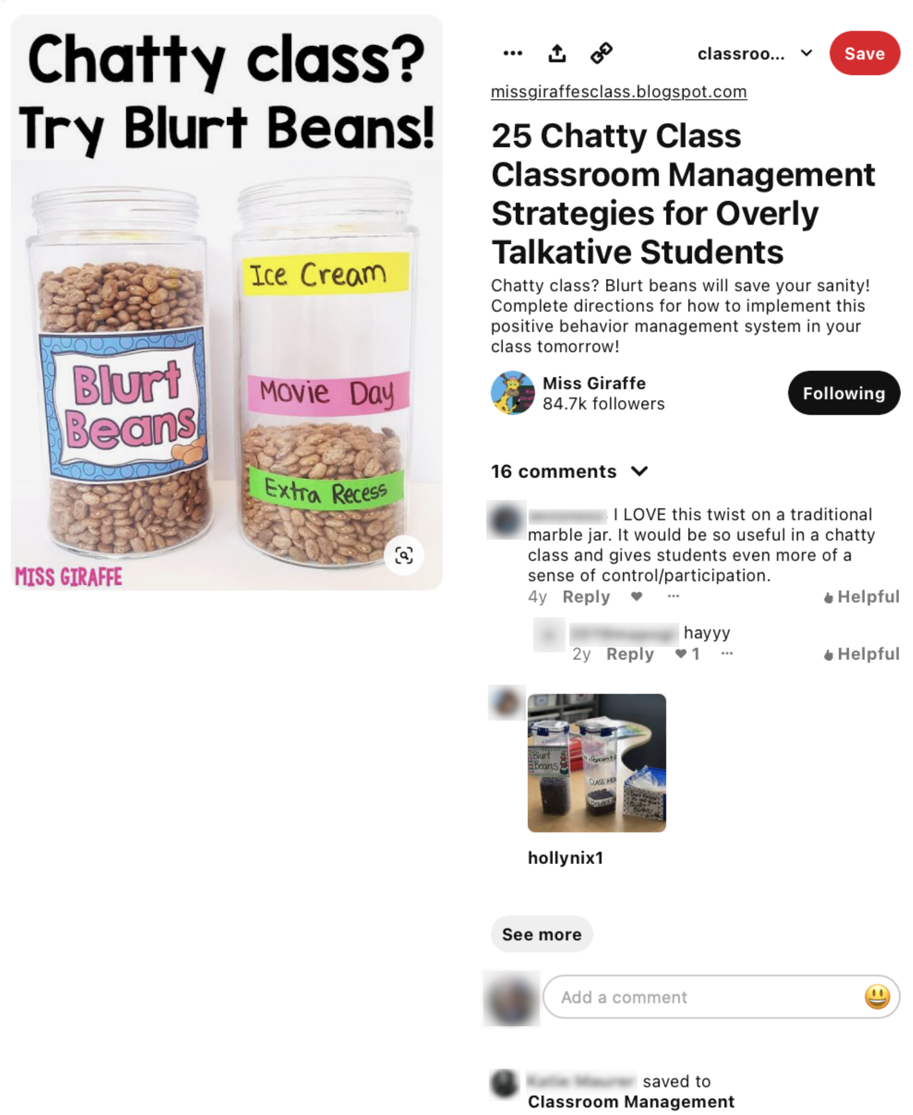
A closer look at a pin's resource space would disclose a variety of content-specific information, including the pin title, pin description, resource image, link to the original creation website, and the content creator. It is worth noting that each pin also contains information on which person saved this pin to one of her personal boards at this round of pinning. To further explain, each pin serves as a documentation of a specific individual's saved resource and her pinning activity that was uniquely identified on Pinterest by its pinning time, the specific pinner, and its pinning board.

In other words, this individual-pinning-specific information reveals to teachers the pinning activity conducted by their network peers, which reflects the curation activities in their social contexts. For situations like various teachers curating the same resource, we would expect that, across several uniquely identified pins, their content-specific information remains the same, while the individual-pinning-specific information would change if we were to compare pins that have originated from the same educational resource but were pinned and circulated via different teachers.

Figure 6 exhibits the most prevalent resource pinned by teachers in the Waters School District. I used it as an example to showcase a pin's resource space. This pin was originally created by Miss Giraffe on missgiraffesclass.blogspot.com before being introduced to the Pinterest platform. The title of the pin is "25 Chatty Class Classroom Management Strategies for Overly Talkative Students," followed by a four-line pin description. There are 16 comments left in the comments section in different forms of texts or images, a majority of which are feedback on or adaptations of the original resources from individuals who tried this idea in their professional contexts. At the bottom of the page is the pinning-specific information, which displayed the name of a teacher from Waters District, who saved this pin to her Classroom Management board. I blurred this teacher's username and photo to protect her data privacy.

Figure 6

An Educational Pin – Chatty Class? Try Blurt Beans!



Teachers' Pinning Activity on Pinterest

There are several ways for teachers to identify resources to pin onto their personal boards. Inside Pinterest, teachers can browse their home feed or use the search bar to find and pin relevant resources based on their interests. Moreover, during the process of teacher-resource interaction, teachers can trace the pinner of this resource and find other content that has also been curated by this pinner via visiting her board or homepage. In a sense, this feature potentially generates network dependencies of further two-mode teacher-resource interactions, which is initiated through visiting the same resource space and expanding to curating more resources from the pinner they encountered in previous rounds of pinning.

Teachers can also pin resources directly from others who they follow in their personal networks, either by visiting their network peers' homepage or by browsing personalized *Updates*, in which Pinterest lists resources pinned by their network peers in chronological order. This following-follower relationship creates an opportunity for social influence effects to occur via interpersonal one-mode networks, in which teachers' pinning activities can be influenced by those with whom they are connected online.

Beyond resource curation inside Pinterest, teachers can also browse and pin image-based resources from external websites, such as Educator Blogs or Teacher-to-Teacher Markets (Torphy et al., 2020), onto their personalized Pinterest boards. Alternatively, teachers can trace resources from Pinterest to external websites and pin them at their creation origin back on Pinterest. In other words, teachers can store and organize resources that are circulated within Pinterest and materials that are created and posted on external websites in one place by pinning them onto their Pinterest boards for a whole collection of curated educational resources. For teachers' resource curation data used in this dissertation, only 1.54% of pins (seven out of 456) are resources teachers pinned from external websites, which indicated that teachers mostly curate resources within Pinterest.

Pinterest Platform Effect

The platform effect refers to the invisible hand of the behind-the-scenes Pinterest recommender system, which affects what resources teachers will be recommended and suggested based on their previous search results, pinning activities, and individuals they followed on personal networks. According to Pinterest Labs (2022), they use featured technologies to enhance their personalization models, which are further explained below, including *AutoML* (a content relevance ranking model), *Interest Taxonomy* (a taxonomy-based content understanding system), *PinSage* (a graph convolutional neural network for web-scale recommender systems), and *PinnerSage* (a clustering algorithm-based user embedding framework).

All machine learning models target personalizing teachers' resource curation experience by considering teachers' previous resource interaction patterns to recommend content that can best fit teachers' interests. For instance, if a teacher starts with "first grade math" in her search box, Pinterest will return results like "first grade no-prep math game for the year," "math 1st grade addition worksheet" etc., with the help of *AutoML*, to expand the query to other similar queries.

As a teacher continues to click on different first-grade-math related pins, each of her interactions with the pin helps the machine learning system—*Interest Taxonomy*—to understand more about the pin and identify topics that better capture the teacher's interest, which is also used to recommend additional relevant content. Then, once the teacher browses through her home feed, Pinterest suggests more first-grade-math inspiration according to her interests. The recommender system works in an iterative fashion, as it gathers and analyzes teachers' resource curation data in each round of teachers' pinning activities.

The *PinSage* algorithm also leverages pinning data from other users who are similar to that teacher regarding their search query in order to continue refining the personalization model. Subsequently, resources that have been pinned by similar others based on the resemblance of their previously curated content will also be suggested to the teacher on their home feed. Likewise, as that teacher starts to create and organize content onto boards, *PinnerSage* recommends her saved pins and boards to others' search queries who are also interested in content relevant to first grade math.

Since the data span of this dissertation for teachers' resource curation on Pinterest was from 2016 to 2017, I traced back to the documentations on the Pinterest recommender algorithm from 2016. This documentation indicated that Pinterest used an earlier recommender algorithm to suggest pins their users may like based on their previous pinning activities. Regarding the above-mentioned four Pinterest recommender algorithms, I found that the earliest time *PinSage* was documented was around 2018, while *AutoML*, *Interest Taxonomy*, and *PinnerSage* were documented around 2020 as the earliest time they could be found on the Internet (Cui & Shrouty, 2020; Hamilton et al., 2017; He, 2018; Pal et al., 2020; Wang, 2020; Ying et al., 2018). In summary, Pinterest applied their earlier version of the recommender algorithm to suggest similar pins in 2016, and further developed a more comprehensive recommender system over the years. Hence, Waters district teachers were subject to the Pinterest platform effect when curating educational resources from 2016 to 2017, though the recommender system was not fully developed at the time.

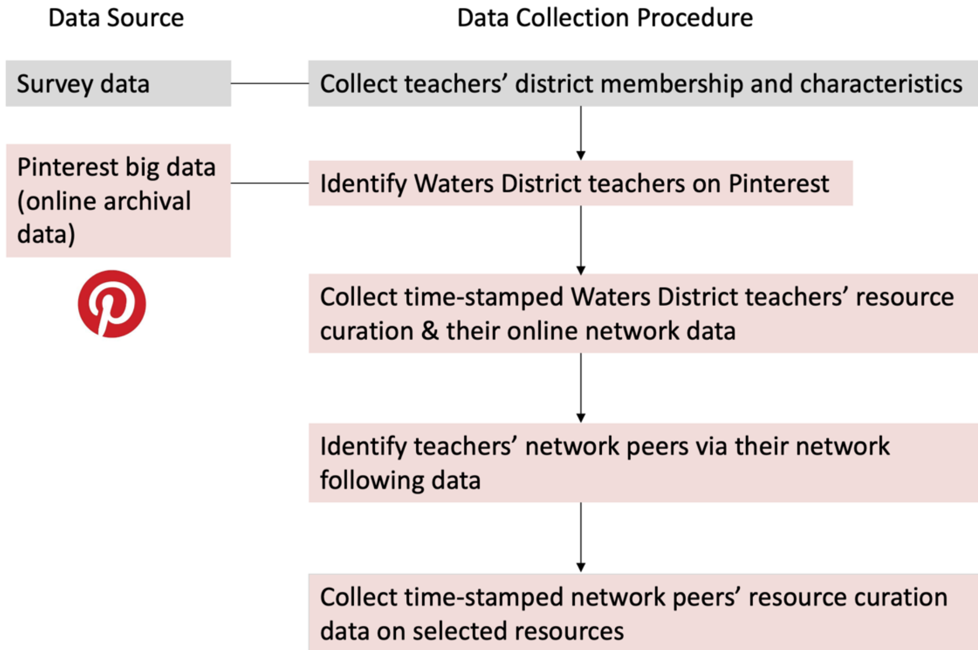
In a nutshell, Pinterest's backend recommender system plays an important yet invisible role, accentuating the clustering effect among similar resources and similar teachers. Specifically, teachers are recommended with resources of similar content on top of their tendency of seeking similar resources that are aligned with their professional values and preferences (see cognitive consistency, Newcomb, 1961). Oftentimes, the clustering effect captures a series of complex higher-order network structural dependencies. In other words, Pinterest catalyzes the phenomenon of cognitive consistency and higher-order network dependencies with its machine learning models.

As resources often function as a social space, individuals who curate similar resources more than expected may also have a higher likelihood of encountering one another, thereby expediting their process of relationship development. Thus, similar teachers tend to cluster as they curate similar resources. In the long run, two-mode-network-wise, the platform effect may cause homogeneity in the types of resources teachers curate and the polarization of groups of teachers as they tend to curate narrowed themes of resources that gather a similar group of teachers.

Data

The data used in this dissertation came from two sources, survey data and Pinterest big data, which were part of the efforts from two collaborative projects: Study of Elementary Mathematics Instruction (SEMI) and Teachers in Social Media (TISM). The SEMI team first employed surveys to collect data on Waters School District teachers (see Sample section below for more descriptions on teachers from the Waters School District) and the TISM team subsequently identified them on Pinterest. The flow chart in Figure 7 shows how survey and Pinterest data were collected in a consecutive manner.

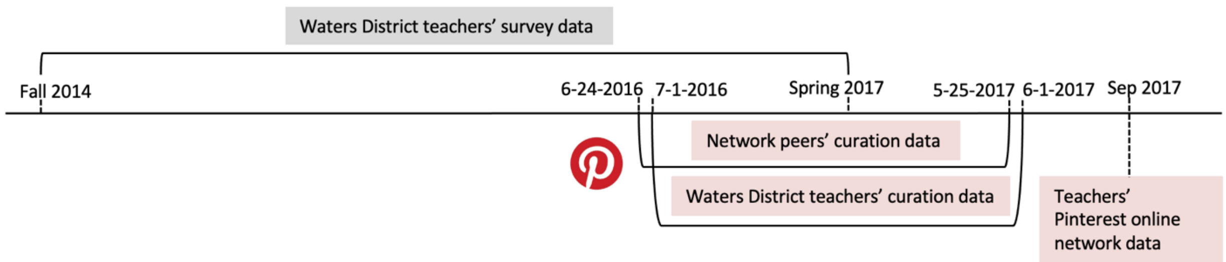
Figure 7
Data Collection Procedure



As this dissertation was part of efforts to study teachers' Pinterest use for educational resources, the method of how teachers' Pinterest accounts were identified and validated can be found in Figure 5 of Torphy et al.'s (2020). Regarding the research ethics of teachers' survey and big data use, we went through the process of de-identifying teachers' names and their Pinterest handles to generate random teacher personal identifiers (PID). Ultimately, the de-identified teacher administrative and social media data were used for research purposes to protect each individual's confidentiality.

The survey data were collected in a progressive fashion, in which Waters District teachers were surveyed over three consecutive years from Fall 2014 to Spring 2017 (see Figure 8). Multiple cohorts of teachers participated in different waves of the survey, though a small group of teachers has been sampled repeatedly over time. I combined teachers from different cohorts and their survey responses for more complete information on teachers from Waters District. Using survey data, we collected information on teachers' school district membership as well as their characteristics, such as their career stage, grade level taught, and so on. Teachers' school district membership was later used to delineate the boundary of the Waters School District on Pinterest's unbounded social space.

Figure 8
Data Collection Timeline



In contrast to the survey data, Pinterest big data was collected retrospectively. Though the online archival data was accessed in September 2017, it provided the opportunity for educational researchers to gather teachers' pinning data starting from the opening of their Pinterest account. Therefore, this dissertation leveraged the capacity of big data to collect Waters District teachers' detailed time-stamped Pinterest curation data of educational resources from July 1, 2016, to June 1, 2017, covering the 2016-17 school year (see Figure 8). This takes into account teachers' tendency to use the summer for lesson preparation and resource-seeking in advance of the beginning of the academic year. This data was used to construct both the teacher-resource two-mode network data as well as the data frame for the relational event model of teacher-resource network ties.

We also downloaded Waters District teachers' Pinterest ego-centric network data including whom they were following by September 2017 (see Figure 8). This was to identify to whom Waters District teachers were exposed in terms of the educational resources in their social context. Ideally, the best time to collect teachers' network data was on or before July 1, 2016, making sure that the network peers' social influence was exerted through an existing tie at the time of the Waters District teachers' resource curation. Alternatively, if teachers' Pinterest following network was found to be relatively stable over time, I could use the network measure in September 2017 as a proxy for teachers' network data in 2016.

Comparing teachers' 2017 and 2018 network data, I found a 95.16% consistency of teachers' network composition over the two years. Among 8129 ties of the 55 Waters District teachers' ego-centric networks, 7736 ties existed across both years (95.16%), with 188 dissolving ties in 2017 (2.31%) and 205 emerging ties in 2018 (2.52%). Due to the limitation at the time of data collection, I only have data downloaded from 2017 through 2018. Based on the examination of network stability across these two years, I assume that teachers' ego-centric networks were also stable from 2016 to 2017. Thus, I used network data in 2017 as a proxy for teachers' network data in 2016.

Once the network peers were identified, we traced to and downloaded their time-stamped Pinterest curation data from June 24, 2016, to May 25, 2017 (see Figure 8). I further subset network peers' curation data on a selected set of educational resources, of which four or more Waters District teachers visited the resource spaces and curated these resources (see more details in the sample exclusion criteria section later). To make a causal statement about the social influence effect, the study design took advantage of the longitudinal time-stamped data and gathered network peers' curation data one week earlier than that of the Waters District teachers to avoid potential confoundedness in the cross-sectional data.

Sample

Waters School District Characteristics

My final analytical sample consists of 55 teachers from nine elementary schools in one Indiana district (Waters District by pseudonym). Based on the reported 2016-17 student demographics from the National Center for Education Statistics (NCES), the Waters School District serves a population of students that are 51.6% male; 27.7% White, 49.9% Black, 13.9% Hispanic, and 0.7% Asian (see Table 1). Moreover, 38.7% of students are eligible for free or reduced lunch. In addition, 3.4% of students in Waters District are English language learners, and 8% of students are in special education. Regarding school-level characteristics, Waters District has a student-to-teacher ratio of 13.96. Among all 18 schools in the district, 83.3% are identified as Title I schools. A sample of teachers from each of the nine elementary schools in Waters District are included in this dissertation.

I compared the student and school characteristics of Waters District to 289 Indiana regular school districts with operating elementary schools (see Table 1). Other than the same proportion of male students, Waters District differs from an average regular school district in Indiana across several characteristics. Specifically, Waters District has 55.5% less White students, 45.7% more Black, 6% more Hispanic, and 0.4% less Asian. Furthermore, Waters District has 0.5% less students eligible for free or reduced lunch, 2% more English language learners, and 0.4% less special education students than an average Indiana school district. Compared to the student-to-teacher ratio of 12.25 in an average Indiana district, a ratio of 13.97 in Waters District marked that teachers in the sampled district taught 1.72 more students on average. In contrast to 29.2% of Title I schools in an average Indiana school district, 83.3% of the schools in Waters were Title I schools.

Table 1
Waters District Comparison with Indiana School Districts and US School Districts

	Waters District	Indiana regular school districts			US regular school districts		
		Obs	Mean	Std Dev	Obs	Mean	Std Dev
Sex – %Male students	0.516	289	0.516	0.014	12,893	0.515	0.037
Race – %White students	0.277	289	0.832	0.184	12,893	0.702	0.276
Race – %Black students	0.499	289	0.042	0.106	12,893	0.069	0.152
Race – %Hispanic students	0.139	289	0.079	0.100	12,893	0.146	0.207
Race – %Asian students	0.007	289	0.011	0.024	12,893	0.021	0.051
%Students eligible for Free Reduced Lunch	0.387	289	0.392	0.017	12,696	0.447	0.115
%English Language Learners	0.034	263	0.014	0.022	9,746	0.032	0.049
%Special Education students	0.080	289	0.084	0.017	12,612	0.073	0.027
Student-to-teacher ratio	13.969	289	12.249	3.655	12,893	12.119	18.940
%Title I schools	0.833	289	0.292	0.294	12,845	0.385	0.388

Beyond the comparisons with Indiana school districts, I also compared the student and school characteristics of Waters District to 12,893 regular school districts with operating elementary schools across the United States (US; see Table 1). Likewise, the proportion of male students remained similar in the sampled district as compared to an average school district in the US. Regarding students' race composition, Waters District has 42.5% less White, 43% more Black, 0.7% less Hispanic, and 1.4% less Asian. Furthermore, Waters District has 6% less students eligible for free or reduced lunch, 0.2% more English language learners, and 0.7% more special education students. With a student-to-teacher ratio of 12.12 from an average US school district, teachers in Waters District taught on average 1.85 more students comparatively. Lastly, Waters District has 44.8% more schools that were Title I, compared to an average US school district (38.5%).

Additional information about Waters District's demographics is provided on the NCES dashboard of education demographic and geographic estimates. Based on data from 2015 to 2019, about one-fifth of the families had income below the poverty level (22.7%) and 21.9% of families received Food Stamps/SNAP benefits. 76.2% of households have broadband Internet. Regarding family types, 43% of families had a Female householder with no husband present, followed by a Married-Couple (41%), a Cohabitating-Couple the next (9%), and a Male householder with no wife present the least (7%). For parents of children in public schools, the median household income was $48,057; 81.7% of them were in the labor force. With respect to parents' educational attainment, a majority were parents with some College or an Associate's degree (37.9%) and High School graduates (31.2%), followed by parents with less than a high school diploma (16.1%) and parents with Bachelor's degree or higher (14.8%).

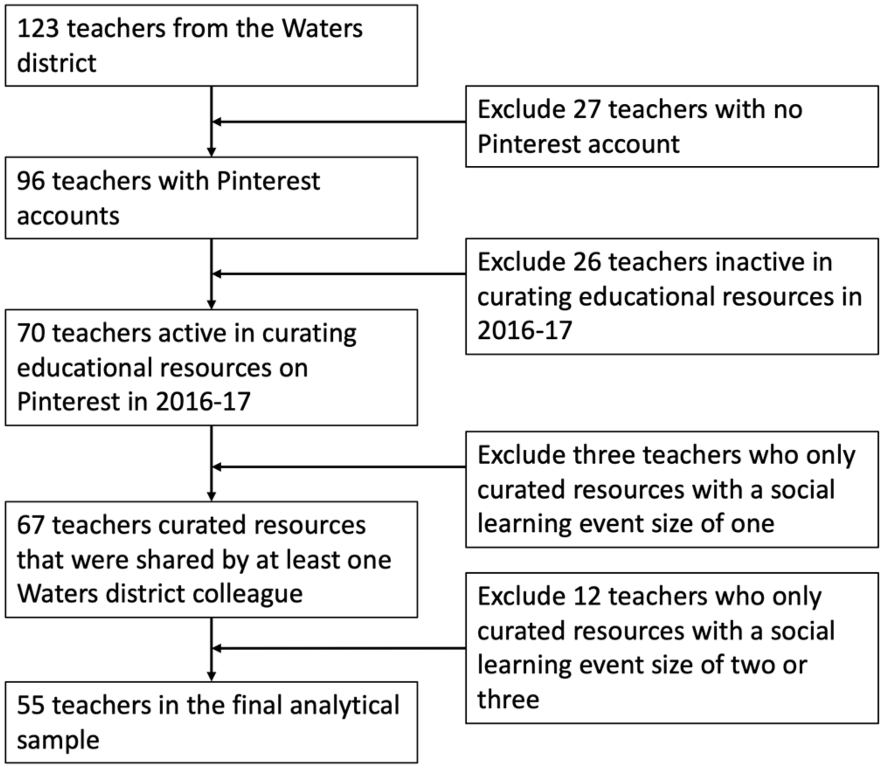
Sample Exclusion Criteria

Teachers investigated in this dissertation were originally sampled by the Study of Elementary Mathematics Instructions (SEMI), which aimed to investigate early career teachers' math instructions and their egocentric collegial networks at school. Using a convenience sampling approach, 123 total elementary teachers from the Waters District agreed to participate in the SEMI study.

This sample was further explored to study teachers' resource curation in an online social space, i.e., Pinterest, a social media platform, under the Teachers in Social Media project (TISM). Thus, teachers who did not have a Pinterest account were excluded (n=27; see Figure 9). In addition, this dissertation focused on teachers' resource curation and their online networks during the 2016-17 school year. Therefore, teachers who were not actively curating educational resources during this period were excluded (n=26).

Figure 9

Sample Exclusion Figure



Furthermore, this dissertation regarded teachers' resource curation as two-mode networks, in which resources are considered as social learning events to connect teachers in online space. Thus, the social learning event size (also considered as the prevalence of a resource among teachers in the Waters District) functioned as a criterion to screen out teachers who only curated resources with a learning event size of one (i.e., resources that were sought by themselves alone). Due to the duality of teachers and resources in the two-mode networks, whether a resource can be qualified as a social event was determined by the number of teachers that have visited and potentially connected in the social space. Therefore, resources with a social learning event size of one were subsequently excluded, as they did not provide a social space for two or more teachers to connect.

Ultimately, 70 Waters District teachers shared 5,169 unique educational resources, among which 87.04% were resources that were only curated by a single teacher. Hence, 4,499 resources with a prevalence of one teacher curating, i.e., having a social learning event size of one, were excluded from the two-mode networks. Subsequently, 3 teachers who only curated resources with a social learning event size of one were excluded, as they were isolated nodes from the entire two-mode social networks and thereby not socially embedded in the two-mode network space (see Figure 9).

Moreover, 589 less-prevalent educational resources were also excluded due to the following concerns in estimating the latent factor model and the relational event model. First, resources that were curated by very small portions of teachers (i.e., two or three teachers relative to 67) in the two-mode networks played a periphery role in determining the primary network structures, while they largely expanded the network size from 136 nodes (55 teachers and 81 resources) to 737 nodes (67 teachers and 670 resources), potentially causing estimation issues in identifying the latent space positions of teachers and resources in the latent factor model.

Second, resources with low curation prevalence or incidence were equivalent to a low hazard rate in relational event models. As teachers' resource curation was modeled across multiple resources and across multiple time points, low incidence of resource curation also created the problem of excess zeros in the logistic regression estimation process, potentially causing models not to converge.

Considering the estimation difficulties, this dissertation set the bounds of the two-mode networks with common resources that were curated by at least four teachers in the Waters District. Therefore, 589 resources were further excluded due to low curation prevalence, i.e., resources curated by two or three teachers. Subsequently, 12 teachers who curated only low prevalence resources were further excluded (see Figure 9).

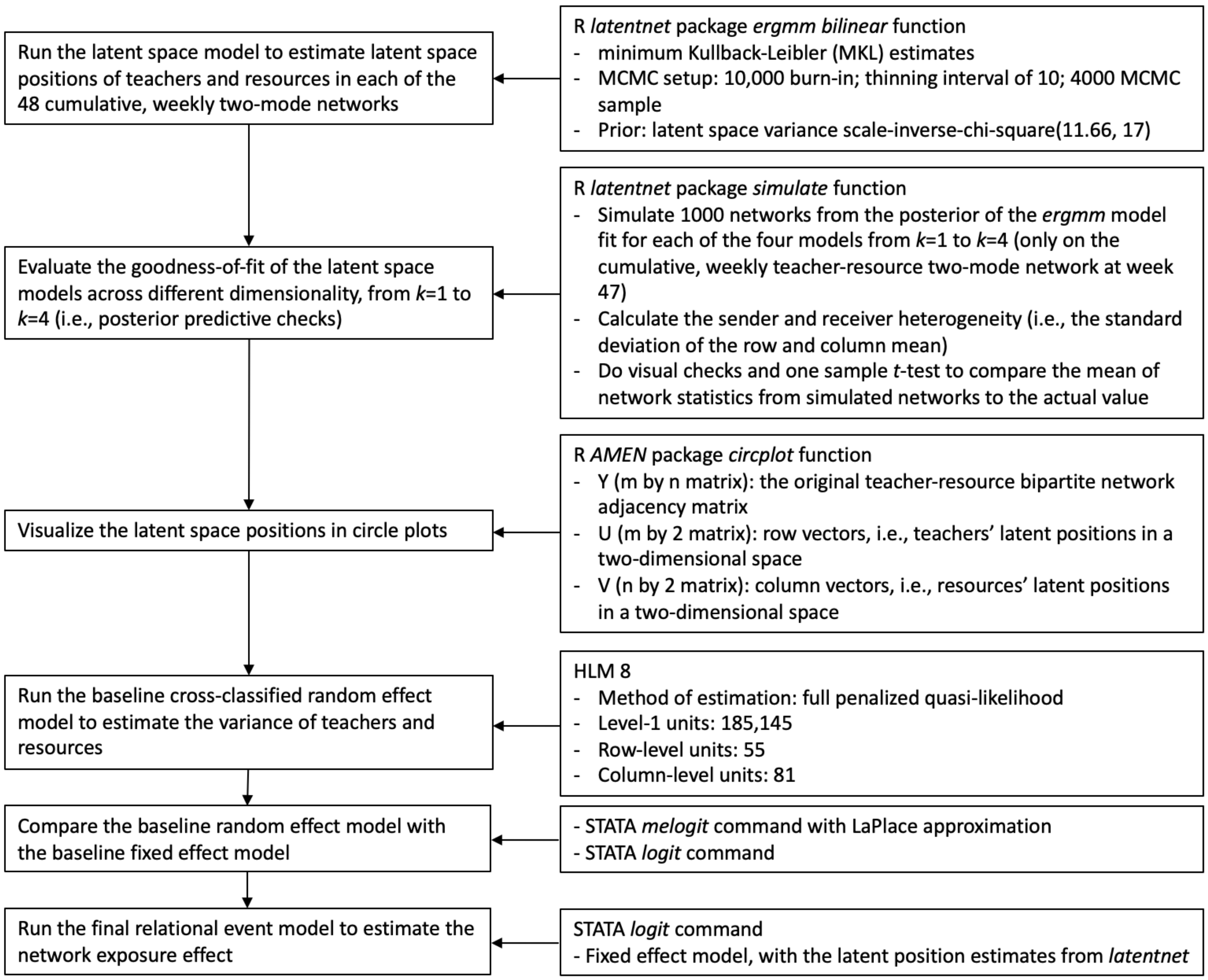
Finally, a sample of 55 teachers and 81 resources was used to represent the joint teacher-resource social space (see Appendix A for 81 resources). For teachers' characteristics, with respect to their school positions, 23 are early career teachers, 27 mentor colleagues, three instructional coaches, one principal and one uncategorized teacher. In addition, descriptive statistics on teachers' grade level taught indicated that 7.27% of teachers instructed kindergarten, 30.91% first grade, 23.64% second grade, 12.73% third grade, 7.27% fourth grade, 3.64% fifth grade, and 1.82% sixth grade. Thus, led by more than half of the teachers from first and second grades (54.55%), there were more teachers sampled from lower grades than from higher grades in this dissertation.

Analytical Strategy

Latent Space Approach with Multiplicative Effects

A latent space approach with multiplicative effects (also called bilinear effects or multiplicative interactions) was employed to first estimate latent positions of teachers and resources in an unobserved social space (see the analytical roadmap in Figure 10). Then the multiplicative effect of teachers' and resources' latent positions was used to account for the network dependency of teacher-resource curation ties in a holistic network structure (Hoff et al., 2002; Hoff, 2005; Hoff, 2009; Hoff, 2018). Specifically, the latent positions were a reduced-rank k-dimensional representation of the original m by n sociomatrix of two-mode teacher-resource network data via singular value decomposition (m represents teachers as rows; n represents resources as columns). Regarding the multiplicative effect $Z_i'Z_j$, it is calculated as the inner product of *teacher i's* and *resource j's* vectors of latent positions, which represents the similarity of teachers' and resources' latent characteristics over a *k*-dimensional space.

Figure 10
Analytical Roadmap



A teacher who carries similar characteristics with a resource has a higher chance to curate that resource and thereby establish a two-mode network tie. For example, the circle plot in the result section (Figure 16) displayed that *teacher*-26 and -36 curated the resources *math-2*, *STEM challenge*-1 and *classroom resource*-1, with two-mode network ties between them, thus being plotted together. This indicated that the two teachers may have a tendency to curate math and STEM related resources, hence sharing similar characteristics with the resources in these categories. Using R package-*latentnet*, I fit the latent space model with bilinear effects (Krivitsky et al., 2020) (see Appendix B for the R code).

To recap the data structure of a two-mode network sociomatrix, rows are teachers and columns are resources. The data in each cell captures whether teacher *I* curates resource *j*. Though sociomatrices record tie-level connections between teachers and resources, a singular value decomposition regards the curated resources of teachers as teachers' characteristics (i.e., treating resource columns as teachers' characteristics) and patterns of teachers being attracted to resources as the resources' characteristics (i.e., treating teacher rows as resources' characteristics). Therefore, by decomposing sociomatrices, the tie-level connection patterns of teachers and resources are translated into node-level latent characteristics of teachers and resources. In turn, the nodal parameters inherently contain teachers' and resources' latent positions relative to others in the entire unobserved social space. Subsequently, their similarities (in a form of vectors' inner product) are used to account for complex network dependencies that involve connections to and between other teachers and resources, of which teachers and resources are embedded.

A previous study showed that homophily between teachers' teaching disposition led to similar resource-seeking patterns on Pinterest (Torphy et al., 2020). Hence, I chose the latent space approach, in which similarities between teachers and resources are modeled by the multiplicative effect, founded on the assumption that homophily or consistency of inherent values between teachers and resources are the driving force behind the resource-mediated social selection process.

Equation 1 is a logistic regression—a probability model for binary network outcomes—to estimate the latent positions Z_i and Z_j. *Teacher-resource tie*$_{ij}$ in equation (1) was the binary network tie between teachers and resources.

$$\text{Logit P(teacher-resource tie}_{ij}=1) = \beta + Z_i{'}Z_j \tag{1}$$

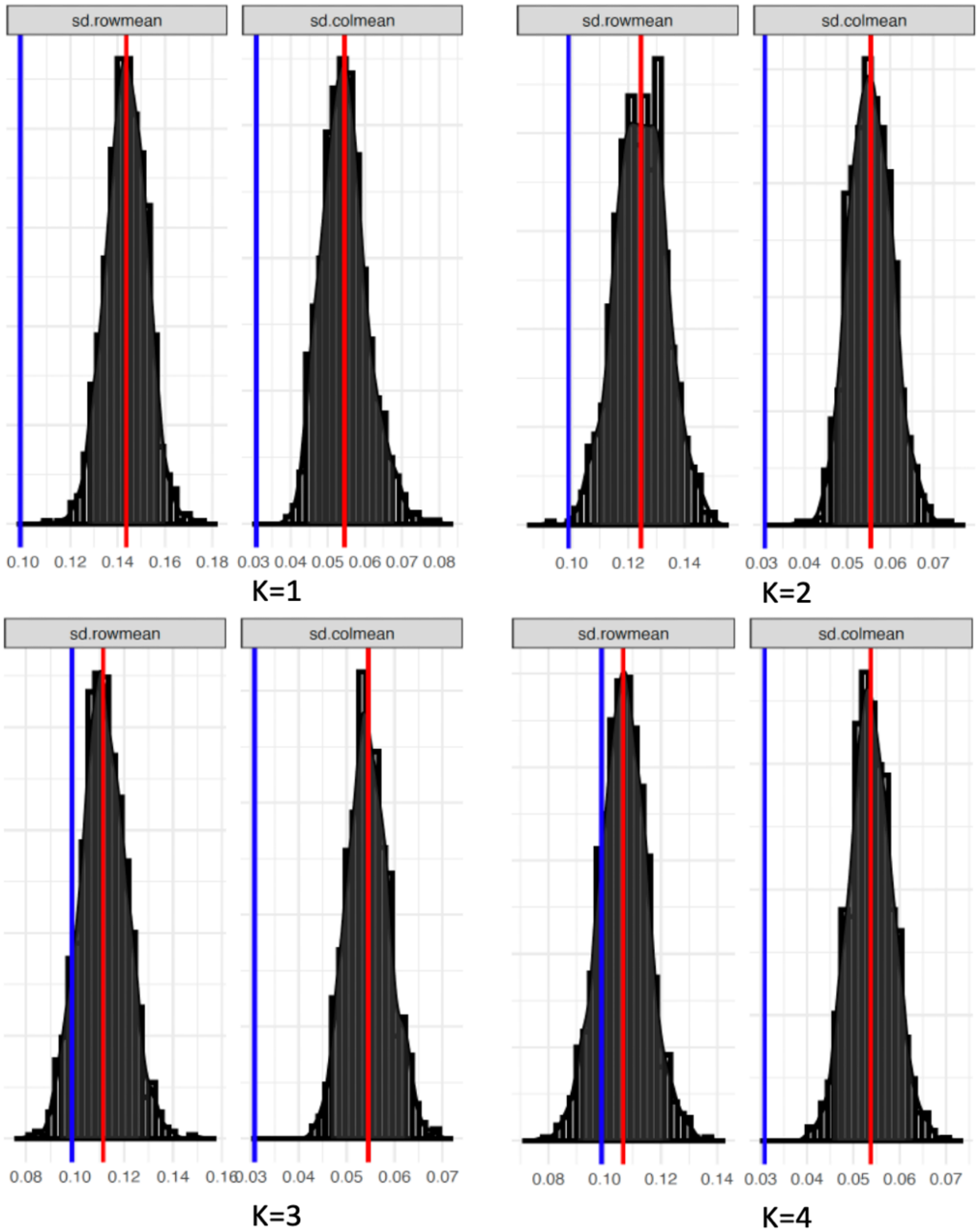
Z_i and Z_j are latent positions of teacher *I* and resource *j* over a *k*-dimensional latent space, of which each is an $m \times k$ and an $n \times k$ matrix respectively. Based on the model fit indices, i.e., Bayesian Information Criterion (BIC), I selected *k*=2 (a two-dimensional Euclidean space) to represent the latent space of teachers and resources. Note that, according to the *latentnet* package, BIC can be safely used to select which fixed effect to include, but it is not clear whether BIC is appropriate to be used to select the dimension of latent space (Krivitsky et al., 2020). Therefore, I also relied on the Markov Chain Monte Carlo (MCMC) diagnostics of latent space models from *k*=1 to *k*=4, specifically the density of the log likelihood, the autocorrelation plot, and the trace plot. Results indicated that except for the week zero estimate (which favored *k*=1), all other 46 weeks' estimations favored *k*=2. For model consistencies, I chose *k*=2 as the dimensions for all latent space models' estimations.

Posterior Predictive Checks on the Model Goodness-of-Fit across Dimensionality. In addition, I conducted the posterior predictive checks to evaluate the goodness-of-fit of the latent space models with different dimensionality (Figure 10). The resulting simulated networks from the *latentnet* were initially in a format of an *n* by *n* matrix, with teachers and resources in both rows and columns (i.e., as both senders and receivers). As the *latentnet* did not set the constraint on the tie generation between different node sets, I further subset an *m* by *n* matrix from the upper right corner of the original simulated networks, to make available the simulated two-mode networks. This approach was equivalent to specifying structural zeros in the original sociomatrix in places where the tie value was *not applicable*. Overall, this preprocessing of the simulated networks was the approach to take for those who wanted to evaluate other two-mode specific network statistics, like the two-mode versions of betweenness and eigenvector centrality, average distance, and transitivity measures.

Based on a sample of 1000 simulated networks for each of the k=1 to k=4 estimated latent space models, I compared a distribution of the predictive sender heterogeneity (the left graph in Figure 11) and receiver heterogeneity (the right graph) to the actual values from the observed teacher-resource two-mode network at week 47. The blue line in Figure 11 denoted the actual value and the red denoted the mean of values from the simulated networks. The shaded intervals represented 90 and 95 percent credible intervals. Visual checks indicated that as the dimensionality k increased, the mean of the predictive sender heterogeneity in red approached closer to the actual value in blue. For receiver heterogeneity, no clear sign of better fit between models of different dimensionality was revealed through visual checks. Thus, I further conducted the one sample t-test and interpreted the results below.

Figure 11

Posterior Predictive Checks on the Sender and Receiver Heterogeneity across Models from k=1 to k=4



In general, the posterior predictive checks showed that the latent space models tended to overestimate the sender and receiver heterogeneity (i.e., teacher and resource heterogeneity). Results from the one sample *t*-test showed that *k*=4 provided the best fit for recovering the sender heterogeneity in the observed network, in which the actual value was 0.0988 and the mean from

1000 simulated networks was 0.1066 with a *t*-ratio of 29.504 (Table 2). In this scenario, *k*=2 was the third best fitted model.

Table 2

Posterior Predictive Checks on Model Goodness-of-Fit across Different Dimensionality

	Sender heterogeneity			Receiver heterogeneity		
	Actual value	Mean value from simulated networks	*t*-ratio (*df*=999)	Actual value	Mean value from simulated networks	*t*-ratio (*df*=999)
	0.0988			0.0308		
k=1		0.1436	166.36		0.0545	124.02
k=2		0.1245	92.695		0.0555	160.35
k=3		0.1115	43.938		0.0545	173.75
k=4		0.1066	29.504		0.0538	160.04

In terms of recovering the observed receiver heterogeneity, the one sample *t*-test result indicated that *k*=1, with a *t*-ratio of 124.02, provided the best model fit, in which the actual value was 0.0308 and the mean of the simulated networks was 0.0545. Nevertheless, the model with *k*=3 generated the same mean (i.e., 0.545) as the model with *k*=1, yet with a larger *t*-ratio. This was because the standard deviation for the column mean (i.e., receiver heterogeneity) of the model with *k*=1 was wider than that of *k*=3, thus *k*=1 had a smaller *t*-ratio—an indicator for a better fit model. This was reflected in the spread of the distribution of the receiver heterogeneity for *k*=1 (a wider spread over 0.08) compared to *k*=3 (a narrower spread over 0.07) (see Figure 11). In other words, the model with *k*=3 had a smaller standard deviation on the column mean, therefore having a larger *t*-ratio—an indicator for a model less than the best fit. The predictive performance of the last three models from *k*=2 to *k*=4 was close.

With respect to the comparison of model dimensionality, *k*=2 appeared to be the third best fitted model in both scenarios. Though *k*=2 may not provide the best fit for capturing the sender and receiver heterogeneity (according to the one sample *t*-test in Table 2), it was the model with the most stable estimation based on visual checks of the MCMC trace plots and autocorrelation plots. Therefore, I chose *k*=2 as the dimension for the latent space model.

Interpretation of Multiplicative Effects. The multiplicative term $Z_i'Z_j$ is a similarity measure between two vectors of latent characteristics of teacher Z_i and resource Z_j. A larger multiplicative effect indicates Z_i and Z_j are similar in their directions, weighted by magnitudes of the vectors. In the context of this study, the magnitude of a teacher's vector represents a teacher's social activity tendency to attend learning events, i.e., curate resources in the online social space of Pinterest. Likewise, the magnitude of a resource's vector represents a resource's prevalence among the group of Waters District teachers.

For example, if teacher *i* is prone to curate classroom management resources, and resource *j* falls into the category of classroom management, we would expect to see a larger-than-expected multiplicative effect as vectors Z_i and Z_j were laid in a similar direction in a *k*-dimensional latent space. In addition, the multiplicative effect becomes larger if teacher *i* actively seeks more educational resources in the social space in general and resource *j* is popular with more teachers curating it.

Clarifying Variation of Terminology across Latent Space Model Literature. Across various phases of latent variable model development, different names have been created in relation to variations of the same technique. To avoid confusion, I will briefly sort out these model terms below. Terms in literature like *latent space approach*, *latent position methods* (Hoff et al., 2002), *latent variable models* (Hoff, 2008; 2018), *latent eigenmodel* (Hoff, 2007), and *latent factor models* (Hoff, 2009; 2018) all refer to the technique of singular value decomposition (e.g. *m* by *n* two-mode networks) or eigen-decomposition (e.g. *n* by *n* one-mode networks) of the observed sociomatrix, with differences of analyzing symmetric versus non-symmetric latent positions as well as one-mode versus two-mode networks. These models are used to compute the singular (or eigen) vectors of teachers and (or) resources as *k*-dimensional vectors of node-level latent characteristics. In this dissertation, I chose to use the term *latent space approach* to keep consistent with the language used in Hoff et al. (2002) R package-*latentnet* (Krivitsky et al., 2020), which provides the option to fit two-mode networks with multiplicative effects.

Terms like *latent positions* are used interchangeably with *latent characteristics* of teachers and resources, both of which carry the meaning of *latent attributes* and *latent features* of nodes in an unobserved latent social space. Furthermore, once the sociomatrix decomposition has been done, terms like *bilinear effects* (Hoff et al., 2002; Hoff, 2005), *projection model* (Hoff et al., 2002), and *multiplicative effects* (Hoff, 2009; 2018) refer to variations of inner products of two latent positions. These are similarity measures of node-specific parameters between teachers and resources, with differences in whether they normalize the magnitude of resource vectors, or in directed one-mode network settings, calculating two latent positions for each person of both their sender's and receiver's roles. According to Hoff (2005, 2018), the "multiplicative effect" is a more generalized form of the "bilinear effect." Thus, I preferred the term *multiplicative effect* for its generalizability and straightforward naming after its functional form—the inner product multiplication of two vectors.

Terminology like *latent space approach* includes both *distance model* and *multiplicative (bilinear) effects model*, in which the former regards a network tie as a function of distance between latent positions of teachers and resources in a Euclidean space; the latter models a network tie as a function of vector similarity between teachers and resources, represented by their latent positions in a Euclidean space. The estimated *latent positions* in a *multiplicative effect model* contain both the direction and magnitude of the teacher- and resource-vectors. The inner product between two vectors represents their similarity and is predictive of the probability of a teachers' resource curation tie. In general, *latent space* is an approach to visualize teachers' and resources' unobserved nodal positions in a latent social space via observed network connections and structures.

In contrast, the *latent factor model*, a further developed *multiplicative-effect latent space model*, is a specific framework for analyzing directed network data. Though both relying on the inner product parameter, the *latent factor model* departed from the *multiplicative-effect latent space model* in that the former estimates two vectors for each node—both a sender's and a receiver's latent characteristics—while the latter estimates only one vector (not distinguishing the sender and the receiver role) for each node as node-specific latent characteristics. Thus, the *latent factor model* focused on directed network data (e.g., non-symmetric one-mode networks), while the *multiplicative-effect latent space model* is more appropriate for undirected network data (e.g., two-mode networks are considered as a type of undirected network). Specifically, *latent factors* refer to the extracted *n*-latent dimensions through decomposing an observed sociomatrix and extracting the corresponding *n*-biggest singular vectors as the new coordinates. In this scenario, *latent positions* refer to the extracted factor scores of nodes and are often visualized in a circle plot (a variation of biplot for network data).

As to the notation for representing the positional parameters, I chose Z_i and Z_j to represent teacher i's and resource j's vectors of latent positions, consistent with the notation in Hoff et al. (2002) and Hoff (2005), which are the two foundational sources of latent space approach development literature. Though the recent development in Hoff (2018) specified the generalized multiplicative effects as $U_i^T V_j$, his main concern is to differentiate two feature vectors (i.e., two latent positions) of the same person i, (i.e., vector U_i and V_i) in asymmetric one-mode networks, in which each person can be simultaneously a sender and a receiver, occurring twice in the latent space. Nevertheless, due to distinct features of two-mode networks in my dissertation, each network tie can only be sent from teachers and received by resources. Hence, only one latent position for each node will be estimated. Therefore, vector $\boldsymbol{Z}$ is adequate to represent the latent positions of both teachers and resources without confusion; there is no need to use $\boldsymbol{U}$ and $\boldsymbol{V}$ to represent senders' and receivers' latent positions separately.

In summary, I chose the *latent space approach with multiplicative effect* to refer to the technique that estimates latent positions of teachers and resources and calculates the inner product of two vectors to account for network dependency. In combining with estimating the social influence effect, a stepwise approach will be taken to first estimate the latent positions of teachers and resources using the latent space model; then I account for its multiplicative effect in the relational event model when estimating the social influence effect of teachers being exposed to their network peers' resource curation. Therefore, I acknowledge the potential pitfall that the stepwise estimation procedure will not be able to simultaneously update the social influence effect and the latent position estimates at the same time.

Estimation. The latent space approach with multiplicative effects assumes that, conditional on the latent positions of teacher *i* and resource *j* in a nonlinear multiplicative fashion, each teacher-resource network tie is conditionally independent of one another. Equation 2 is the likelihood function for a conditional dyadic independence model, in which the binary outcome—teacher-resource two-mode network tie—followed a Bernoulli distribution.

$$L(Y;\theta) = P_\theta(Y=y) = \prod_{i\neq j} P(y_{ij}|\theta) = \prod_{i\neq j} \frac{\exp(\eta_{ij}(\boldsymbol{\theta})y_{ij})}{1+\exp(\eta_{ij}(\boldsymbol{\theta}))} = \frac{\exp\left(\sum_{i\neq j}\eta_{ij}(\boldsymbol{\theta})y_{ij}\right)}{\prod_{i\neq j}(1+\exp(\eta_{ij}(\boldsymbol{\theta})))} \tag{2}$$

Equation 3 incorporated the model specification from (1) to (2), in which I explicitly specified and substituted the function of parameters $\eta_{ij}(\theta) = \beta + Z_i^T Z_j$.

$$L(Y;\theta) = P_\theta(Y=y) = \prod_{i\neq j} P(y_{ij}\big|Z_i, Z_j, \beta) = \frac{\exp\left(\sum_{i\neq j}(\beta+Z_i^T Z_j)y_{ij}\right)}{\prod_{i\neq j}(1+\exp(\beta+Z_i^T Z_j))} \tag{3}$$

Equation 4 is the log-likelihood function of (3), which was maximized to get the maximum likelihood estimates of latent positions Z_i and Z_j.

$$\log \mathrm{P}(\mathrm{Y}|Z,\beta) = \sum_{i\neq j}\left(\left(\beta + Z_i^T Z_j\right)y_{ij} - \log\left(1 + \exp\left(\beta + Z_i^T Z_j\right)\right)\right) \qquad (4)$$

The Bayesian method, in combination with the Kullback-Leibler divergence, was used for estimating the latent positions of teachers and resources. Regarding the estimator, the minimum Kullback-Leibler (MKL) estimates of (Z, β) were produced, which minimized the posterior mean of the Kullback-Leibler divergence from the true model. The true model refers to the model with parameters given by the posterior expectation of the network graph under the mean-value parameterization of the exponential family model. Briefly speaking, the Kullback-Leibler divergence is a general measure of the difference between two distributions—the joint probability of the posterior distribution of the network graph with parameter ϕ (i.e., from the true model) versus that distribution with parameter η, in which η=(Z, β) (i.e., the MKL that needs to be estimated). According to Shortreed et al. (2006), the minimization problem of the Kullback-Leibler divergence with respect to η then becomes a maximization problem, which is simplified to finding the value of η (i.e., Z, β) that maximizes $\frac{exp\ (\eta^T E[Y|Y_{obs}])}{c(\eta)}$. Furthermore, Shortreed et al. (2006) indicated that the posterior mean E$[Y|Y_{obs}]$ can be accurately obtained from the MCMC samples.

The Bayesian method is used for estimating the posterior probability distribution of the latent positions of teachers and resources. The set-up for the Markov Chain allows 10,000 iterations for burn-in, which were discarded and not used for the posterior density. Drawing every 10^{th} of the sample from a 40,000-sample Markov Chain, the posterior density of the parameters contained an ultimate sample of 4000.

The latent position *Z* is set to be a mean-zero random effect. As the network size increased, the prior distribution for the latent space variance also increased and was proportional to the number of nodes in the network. With respect to the specific cumulative, weekly network at week 47, the prior distribution for the overall latent space variance is scale-inverse-chi-squared (11.66, 17), with 11.66 as the number of Chi-squared degrees of freedom and 17 as the scaling parameter. These are the parameter values chosen by the *latentnet*. In other words, the mean for the latent space variance is set at 20.52, with a variance of 109.92, considered as an informative prior.

According to Krivitsky and Handcock (2008), a larger value of the latent space variance leads to "lower belief in cluster separation," and a lower value of the latent space variance degrees of freedom represents "greater diversity in within-group variation." They further illustrated that too high a prior latent space variance "leads to clusters blurring together," while too low a variance "creates posterior mode in which all the clusters are concentrated at a point, causing the fit to collapse." Since I only estimated a model with one cluster, treating all teachers and resources in the same group, blurred clusters are less of a concern. Thus, specifying the variance at a value higher than 17 can be another alternative. Regarding the variance degrees of freedom, an alternative specification can be a value higher than 11.66, as I did not expect any diversity in within-group variation, given that I only fit a model of one group. I also fitted a model with an uninformative prior of scale-inverse-chi-squared (1, 100). The model converged, indicating the posterior density did not strongly depend on the prior. In fact, a 55 by 81 network has 4455 tie-level observations. This means the posterior density was dominated by the likelihood function of the data and was less influenced by the prior specification. Beyond the latent space variance, the prior distribution on the intercept β is normal (0, 9).

The MKL estimates have been shown to be superior to the other three alternative latent position estimates, i.e., the maximum likelihood, the posterior mean, and the posterior mode. First, the MKL estimates produced more consistent network statistics, like density, compared to the observed networks, indicating that the MKL estimates are a better representation of the latent positions. This is particularly true when comparing the MKL estimates to the posterior mean and the posterior mode estimates. Second, due to statistical averaging and use of prior information, oftentimes models with MKL estimates will be closer to the true model, compared with the maximum likelihood estimate (Shortreed et al., 2006). Third, as the 2020 *latentnet* package indicated, MKL estimates were used as the default methods. Thus, I chose the MKL estimates as the positional estimates of teachers and resources in the latent space.

Variable Description

Dependent Variable

Regarding teachers' resource curation, I used whether teachers pinned a particular resource or not as the dependent variable (M=0.002, SD=0.047; see Table 3). With the longitudinal data capacity, I transformed teachers' time-stamped resource curation data into a time frame of 48 weeks, each week indicating whether or not a teacher pinned a resource (Singer and Willet, 2003; De Nooy, 2011). Along with 55 teachers' resource curation data over 81 resources, the complete data framework for the dependent variable is on the basis of all three dimensions, i.e., 55 teachers x 81 resources x 48 weeks = 213,840 observations. A value of one indicates whether teacher i pinned resource j at week t.

Table 3

Descriptive Statistics for Variables in the Regression Analyses

	N	M or Percent	SD	Min	Max
Teachers' resource curation (i.e. teacher-resource ties)	185,145	0.002	0.047	0	1
Network exposures					
Network exposure (overall)	185,145	0.093	0.858	0	44
Network exposure to school-and-district colleagues	185,145	0.009	0.105	0	3
Network exposure to online-only peers	185,145	0.084	0.850	0	44
Similarity of teachers' and resources' latent positions (vectors' inner product)	144,117	-0.197	0.769	-5.012	5.068
Missing indicator for the similarity of latent positions	185,145	0.222	0.415	0	1
Low curation volume indicator	48	0.167	0.377	0	1
High curation volume indicator	48	0.167	0.377	0	1
Teachers in early career stages	55	0.418	0.498	0	1
Grade	48				
Lower-elementary	21	43.75%			
Mid-elementary	20	41.67%			
Upper-elementary	7	14.58%			
Resource type	81				
Subject-Specific	31	38.27%			
Classroom Management	17	20.99%			
Classroom Resource	12	14.81%			
Social & Emotional Learning	21	25.93%			
Resource origin	81				
Educator's Blogs	57	70.37%			
Teacher-To-Teacher Consumption Markets	12	14.81%			
Periphery Online Secondary Sites	6	7.41%			
Educational Organizations	6	7.41%			
Teachers' perceptions of teaching					
Effective teaching disposition	42	3.024	0.517	2	4
Competency in classroom management	39	3.256	0.549	2	4
Perceived helpfulness of state test expectations	41	3.268	1.049	1	5
Pervasive beliefs among teachers that students aren't motivated to learn	38	1.789	0.991	1	4

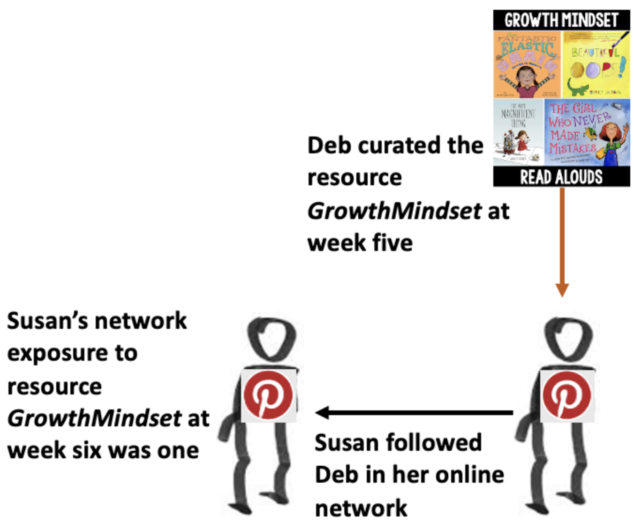
In addition, the relational event model assumes that the event of teachers pinning a particular resource can only happen once in the time of a study. Thus, once teachers pinned a certain resource, they hit the hazard of resource curation. These teachers will no longer stay for further pinning of the same resource and are dropped out of the risk set. This is a reasonable assumption as teachers' resource curation activity is mainly to search, store, and organize resources on their personalized Pinterest boards to be used in the future. Based on this model assumption, I censored teachers' resource curation data after the week of them pinning a specific resource, resulting in 201,315 observations. Lastly, not all resources were created before the beginning of the study. I further tailored the data frame, deleting observations of teachers' resource curation for the week in which resources had not been made available to pin based on the resource creation time (final observations were 185,145).

Independent Variables

Network Exposure. Teachers' network exposure—$\Sigma_{i'}$teachers' following network tie$_{ii'}$×online peer's resource curation$_{i'j(t-1)}$ —is defined as the number of times an online network peer *i'* curated the resource *j* at an earlier week *t-1*, summed over all network peers of teacher *i* (*M*=0.093, *SD*=0.858; see Table 3). In other words, the network exposure term is composed of two elements: network connections between teacher *i* and network peer *i'*, and resource curation activities conducted by peer *i'*. The network exposure term was designed to be resource-specific and time-specific, in which only network members' curation activities on the same resource in the most recent week were qualified as teachers' exposed network influence. For example, Susan has a network of two peers with Rachel and Deb, who pinned resource *GrowthMindset* at week three and week five respectively. The network exposure of Susan to resource *GrowthMindset* at week six would be a value of one. In this scenario, only Deb's curation of this resource is counted as Susan's network exposure due to Deb's pinning in the most recent week (at week five), which directly precedes Susan's week six resource curation activity (see Figure 12).

This is because Susan is most likely to be exposed to resources pinned by her online networks in the most recent week, as Pinterest ranks and recommends the most recently curated resources of network peers to be displayed on Susan's main page and in her notification updates. I also created a cumulative network exposure measure, aggregating all network peers' curation activity on the same resource since the beginning of the study. The zero-order correlation indicated that the network exposure of the most recent week was positively and significantly correlated with the cumulative network exposure at r=0.679—each of them was positively correlated with the dependent variable, i.e., the first occurrence of a teacher curating a resource, at 0.015 and 0.013 respectively.

Figure 12
Susan's Network Exposures to Resource GrowthMindset at Week Six



The dynamic nature of online peers' curation activities and subsequently teachers' network exposure to their curated resources illustrated a constantly changing resource curation social environment in teachers' online networks. This dissertation regards resources curated by network peers in the most recent week as having the most salient social influence effect on teachers' resource curation activity in a given week. Teachers on average connected with 144.07 people on Pinterest, and on average received 0.093 network exposures per resource each week.

The maximum teachers' network exposures from online networks to a resource in a given week was 44.

Network Exposure to School and District Colleagues and Online-Only Peers. To test hypotheses on separate network exposure effects from school and district colleagues, as well as online-only peers, I split each weekly overall network exposure term into two, based on whether the exposures were from school and district colleagues (*M*=0.009, *SD*=0.105; see Table 3) or from online-only peers (*M*=0.084, *SD*=0.850; see Table 3). So, for every one network exposure from school and district colleagues, teachers received 10 times the amount of network exposures from online-only peers. Teachers on average connected with 5.65 school and district colleagues, and 138.42 online-only peers. The maximum network exposures teachers received in a given week from school and district colleagues and from online-only peers were three and 44 respectively. Descriptive statistics indicated that the network exposures teachers received from each group were proportional to the number of people in that group.

The Similarity of Latent Space Positions. The similarity of teachers' and resources' latent positions was calculated using the inner product of vectors of teachers' and resources' positions along two dimensions of the latent space (*M*=-0.197, *SD*=0.769; see Table 3). Considering the time dynamic of two-mode networks of teachers and resources, their latent positions were likely to be changed in a weekly manner as more teachers joined to curate a variety of resources, and more resources became available as time elapsed. In addition, teachers' resource curation ties at week *t* not only depended on other curation ties in the current week but was also subject to the impact of teachers' curation ties formed in the weeks since the beginning of the study. Therefore, the latent space positions of teachers and resources were calculated in a weekly and cumulative fashion. For the first week (i.e., week zero), teachers' and resources' latent positions and their similarities were only based on the two-mode network of that week. From the second week (i.e., week one) to the 48th week (i.e., week 47), latent positions and their similarities were computed from a cumulative curation network that aggregates network ties from previous week(s) to the current week; for example, the cumulative two-mode network in the second week combines ties from the first and second week. This is to account for network dependencies accumulated over time.

Dealing with Missingness in the Similarity of Latent Space Positions. Though ultimately 55 teachers and 81 resources were present in the two-mode networks over the period of one school year, not all teachers curated resources from the beginning of the study, nor had all resources been pinned in the first week. Hence, both were absent in the two-mode network in the early weeks until teachers gradually joined to pin resources in the social space and resources were introduced by teachers to the two-mode network. In these scenarios, teachers and resources as nodes in two-mode networks were missing, further creating a missing-tie issue between teachers and resources, causing the missingness of their latent positions and similarities in the given week.

Yet, teachers experienced a hazard of pinning a particular resource even though their latent positions were not identified. To avoid listwise deletion in estimating the network exposure effect, I assume that latent positions among absent teachers and resources are the least similar in any given cumulative, weekly two-mode network. In other words, they are the least likely to have a resource curation tie. I imputed the minimum value of the observed similarity of latent positions between teachers and resources in a given week to those teachers and resources that are absent in that two-mode network. I also included a missing indicator (M=0.222, *SD*=0.415; see Table 3) in the final model to account for the variation in teachers' resource curation attributed to the measurement inaccuracy in the variable *similarity of latent positions*.

Covariates

Time. I chose weeks to be the natural time unit as teachers tended to systematically curate resources for lesson planning and instructions on a weekly basis. The first week (July 1, 2016) was set to be a value of zero, as the starting point of planning for the upcoming school year. The following weeks were arranged in sequence to week 47 (June 1, 2017) based on the Waters district school calendar.

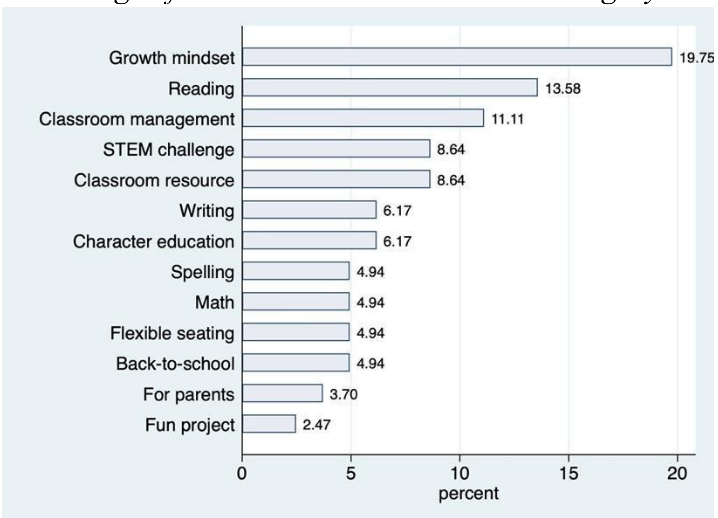
Extreme Resource Curation Weeks. Previous research has found seasonal effects and fluctuations on teachers' resource curation activities during different times of year (Torphy et al., 2017). Thus, I created two indicator variables to account for lowest and highest curation volumes at the weekly level. I used the cut-off score based on teachers' curation volumes at the 17.44 and 84.71 percentile to distinguish the lowest and highest volumes. Specifically, if a week has teachers curating resources less than three times, that week is labeled as one of the weeks with the lowest curation volumes. They are the weeks of December 2, December 9, January 20, March 3, and of April 7 through the week of April 28 (covering the entire month of April). Likewise, if a week has teachers pinning resources more than 15 times, that week is labeled as one of the weeks with the highest curation volumes. They are the weeks of July 1 through the week of July 22 (the entire month of July), and the weeks of August 12, August 26, December 30, and March 24.

Teacher's Career Stage. According to Torphy et al. (2020), using a sample of 100 teachers from four school districts, they found that teachers in different career stages (i.e., early career teachers compared to experienced teachers) tend to curate resources differently, with early career teachers having an online resource portfolio similar to those of others in their local area, while experienced teachers have a more independent resource portfolio. Hence, I created an indicator variable, labeling if a teacher is in an early career stage (i.e., those who were in their first three years of teaching) (*M*=0.418, *SD*=0.498; see Table 3).

Teacher's Grade Level Taught. Previous studies have found that the grade level taught significantly predicts the curation similarity between teachers (Torphy et al., 2020). This finding indicates that teachers from different grades tend to seek different resources. Thus, I included the grade level taught to reduce its confoundedness with the network influence effect as teachers are more likely to follow network peers in the same grade who appeared to curate the same resources. Due to concerns of the non-linear relationship between the grade level taught and teachers' resource curation, I further grouped grades into three categories: lower grades (grades kindergarten to one; 43.75% of the teachers; see Table 3), mid grades (grades two to three; 41.67% of the teachers), and upper grades (grades four to six; 14.58% of the teachers). The category *lower grades* was set to be the reference group.

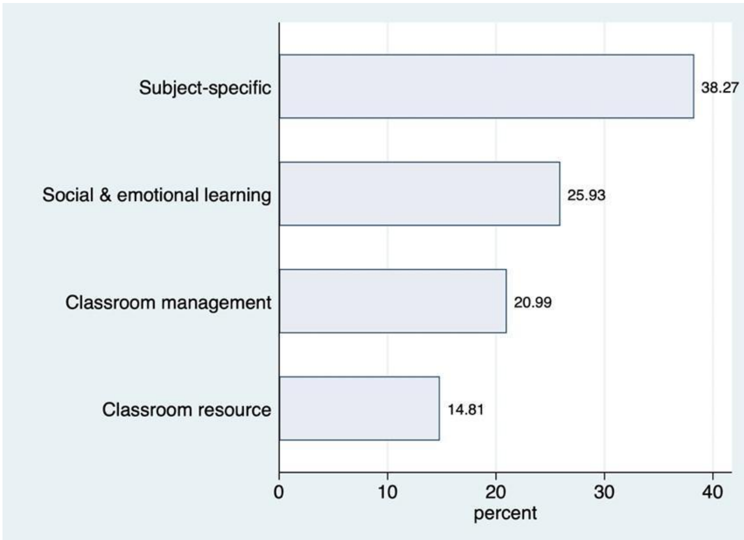
Resource Category. Resource content was coded based on the pin description and the text and graphs embedded in the pin image. There were 13 resource categories found in the coding process. Results indicated that the most prevalent resource content was Growth Mindset (19.75%), succeeded by Reading (13.58%) and Classroom Management (11.11%) (see Figure 13). The second tier of frequently curated resources included STEM Challenge (8.64%), Classroom Resource (8.64%), Writing (6.17%), and Character Education (6.17%). Lastly, resource content that was curated by less than 5% of the Waters school district teachers were in categories such as Spelling (4.94%), Math (4.94%), Flexible Seating (4.94%), Back-to-school (4.94%), For Parents (3.7%), and Fun Project (2.47%). The coded resource categories were used for displaying the name of the resources and their latent positions on the circle plot of weekly, cumulative two-mode networks.

Figure 13
Percentage of Resources in Each Content Category



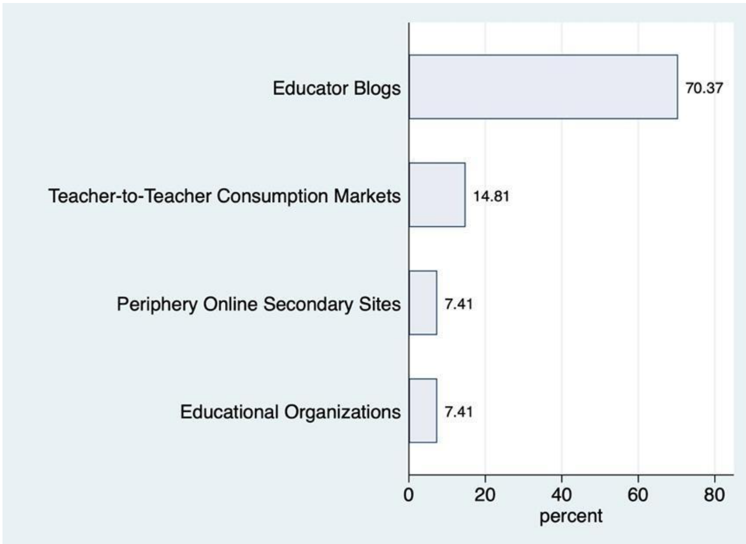
Resource Type. I further combined the 13 content categories into four broader resource types (see Figure 14). The most prevalent resource type was the Subject-Specific (38.27%; see Table 3), including Reading, STEM Challenge, Writing, Spelling, and Math. The second leading type was Social and Emotional Learning resources (25.93%), including Growth Mindset and Character Education. Next was Classroom Management-relevant resources (20.99%), including Classroom Management, Flexible Seating, and Back-to-school. The least frequently curated type was Classroom Resource-relevant resources (i.e., facilitating materials) (14.81%), including Classroom Resource, For Parents, and Fun Project. In summary, when resources were coded at the broader content level, the most prevalent resources shifted from Growth Mindset to Subject-Specific resources. The combined resource type was used in the final relational event model to account for variations in teachers' resource curation attributed to teachers' preferences of certain types of resources. S*ubject-Specific resource* was set to be the reference group.

Figure 14
Percentage of Resources in Each Resource Type



Resource Origin. As a content curation platform, Pinterest pooled a variety of image-based content from websites outside of its platform. This content embodied the standing and professional beliefs of the original content creators. Thus, I adopted the coding framework developed by Torphy et al. (2020) to characterize resources based on their resource origin (aka secondary online sites). Categorizing 81 resources into four groups, the classification results indicated that 70.37% of the resources were originally from Educator Blogs, e.g. Missgiraffesclass (see Table 3, Figure 15). The next group was resources from Teacher-to-Teacher Consumption Markets (14.81%), e.g. Teacherspayteachers; followed by resources from Periphery Online Secondary Sites (7.41%), e.g. YouTube and Facebook; and Educational Organizations (7.41%), e.g. Scholastic. Compared with the percentage distribution of the resource origins of 140,287 coded pins in Torphy et al. (2020)'s article, data in this dissertation contained 12% more resources from Educator Blogs, a similar percent of resources from Teacher-to-Teacher Consumption Markets and Educational Organizations, while having 11.5% fewer resources from Periphery Online Secondary Sites. *Educator Blogs* was set to be the reference group.

Figure 15
Percentage of Resources by Origin



Teachers' Perceptions of Teaching. Four items from the Waters District teachers' survey on their perceptions of teaching were used in the exploratory analyses on the interaction effect of network exposure and teachers' perceptions of teaching. Teachers' survey data were combined across cohorts that responded in one or more waves of the survey from 2014 to 2017. For those who participated in multiple years, I used their responses in 2016 to best align with their resource curation activities during the same year. Though the survey was to measure teachers' perceptions on mathematics instruction, elementary teachers tend to teach multiple subjects at the same time. Thus, I used their survey responses as a proxy for their general perceptions of teaching.

Effective Teaching Disposition. The original survey item was in a 4-point Likert scale and asked teachers to what extent did they agree with the following, "when the mathematics grades of students improve, it is often due to their teacher having found a more effective teaching approach" (M=3.024, SD=0.517; see Table 3).

Competency in Classroom Management. This 4-point Likert scale item asked about the perception of teachers' general teaching ability regarding to what extent they agreed with "if a student in my class becomes disruptive and noisy, I feel assured that I know techniques to redirect him/her quickly" (M=3.256, SD=0.549; see Table 3).

Perceived Helpfulness of State Test Expectations. This 5-point Likert scale item asked "on average across all of your mathematics lessons when you most recently taught, to what extent did expectations associated with state math tests support or inhibit your ability to enact your math lessons" (M=3.268, SD=1.049; see Table 3).

Pervasive Beliefs among Teachers that Students Are not Motivated to Learn. This item asked, on a 5-point Likert scale, about what percentage of teachers at your school shared the following belief, "students at this school just aren't motivated to learn" (M=1.789, SD=0.991; see Table 3).

Teachers' and Resources' Indicators. To account for possible unique resource curation patterns specifically related to certain teachers or resources, I generated teachers' and resources' indicator variables. In the context of network analysis, teacher- and resource-effects are also called sender- and receiver-effects, which captures teachers' tendency of curating a resource and resources' tendency of being curated. To simplify the number of indicators used for teachers and resources, I created indicators based on teachers' outdegree and resources' indegree (i.e., the number of ties sent by teachers and the number of ties received by resources). See Table 4 for the teachers' outdegree and resources' indegree frequency table. For example, if Mary and Bob were both curating seven different resources, they would be labeled with a value of one on the same indicator for an outdegree of seven. A similar approach was used to group and label resources based on having the same number of teachers curating certain resources. A likelihood ratio test showed that the model controlling for all teachers' and resources' fixed effects (with 134 fixed effects) is not significantly different from the simplified model that only controlled for indicators of teachers' outdegree and resources' indegree (with 25 fixed effects), $\chi^2(109)=18.38$, $p>.05$.

Hence, I chose the parsimonious specification with similar model performance.

Table 4
Frequency Table of Teachers' Outdegree and Resources' Indegree

	N	Percent
Teachers' outdegree	55	
1	12	21.82%
2	3	5.45%
3	5	9.09%
4	6	10.91%
5	3	5.45%
6	7	12.73%
7	3	5.45%
8	3	5.45%
10	1	1.82%
11	1	1.82%
12	1	1.82%
13	3	5.45%
17	1	1.82%
22	1	1.82%
23	1	1.82%
24	1	1.82%
30	1	1.82%
31	1	1.82%
33	1	1.82%
Resources' indegree	81	
4	43	53.09%
5	16	19.75%
6	11	13.58%
7	5	6.17%
8	3	3.70%
9	1	1.23%
12	1	1.23%
13	1	1.23%

Using the Relational Event Model to Estimate Network Influence

Using a logistic regression for discrete-time relational event models, I estimated the network exposure effect on teachers' resource curation, while accounting for similarities of latent positions between teachers and resources in an unobserved two-mode social space. *P(teacher-resource* $tie_{ijt}=1|$*teacher-resource* $tie_{ijs}=0, s<t$*)* was the discrete-time hazard for teacher *i*

curating a resource *j* at time *t*, i.e., a time-specific teacher-resource tie, given that all previous relational events leading to this tie were absent—*resource curation*$_{ijs}$=0 (see Model 1-1). In other words, teacher *i* remained at risk of curating resource *j* over the period of *s* until they curated the resource at time *t*, i.e., *teacher-resource tie*$_{ijt}$*=1*. Notation *s* covered all previous episodes of potential relational events in a weekly manner, from the beginning week t_0 to a week *t-1* (before the current week *t*). At the week *t* of teacher *i* curating resource *j*, the teacher encountered the relational event, in which the data of this week would be used to calculate the hazard of teachers' resource curation against all previous episodes of non-occurrence.

Once teacher *i* pinned resource *j*, they were no longer at risk. All following episodes related to teacher *i* and resource *j* were set to missing and would not be used to calculate the hazard rate of resource curation (see also descriptions of *the dependent variable*). For example, if Bob has already curated a math resource at week one, he has hit the hazard of curating that resource and will be dropped with no observations in further weeks i.e., from week two to week 47. The relational event model assumes that once a teacher curates a certain resource, they remain in the state of possessing the resource. In other words, the state of resource possession cannot reverse back to the state of non-possession.

In addition, the relational event model assumes that teachers can only curate the same resource once in the study period. Given a low incidence of repeated pinning in my data (i.e., 0.006, 28 cases in 4455 possible pinning events), I decided to use the discrete time hazard model over the multiple-spell discrete time hazard model. For concerns about teachers curating resources in a repeated fashion, I included teachers' fixed effects to account for the heterogeneity in teachers' curation preferences. See Liu et al. (2020) for more information on four different specifications of teachers' resource curation activities (including first occurrence of teachers' resource-pinning activity, repeated occurrence, and teachers' cumulative resource possession). For teachers who did not curate that resource over the entire 48-week time interval, their values of resource curation would be zeros across all 48 weeks and censored at the end of the study. B_0 is the baseline hazard at the beginning week.

Concerns for Controlling for Prior Behavior

Regarding the causal inference on the network influence effect, a typical approach is to control for the prior teachers' resource curation activity—prior teacher-resource ties—with the aim to account for teachers' own stable curation patterns in the past (and all other factors that caused teachers to curate what they have curated). Controlling for the prior helps to alleviate the concern of confoundedness when estimating the network influence effect. Nevertheless, in the relational event modeling framework, this is less of a concern by virtue of the built-in model assumption that the current tie occurrence is conditional on the fact that all previous ties have not occurred, thereby inherently controlling for the prior behavior. In other words, the relational event modeling framework assumes that each current observation of a teacher-resource tie is inherently conditional on the fact that teacher *i* has not curated resource *j*, i.e., $resource\ curation_{ijs}$=0, since the beginning of the study. This means there would be no variation in the prior behavior measure of all teachers over all resources if it were included in the model.

Second, as the motivation of teachers' resource curation activity is information seeking, teachers are most likely to curate resources they have not encountered before, which indicates that teachers had little to no prior experience curating this resource. Third, I regarded the start of each school year as a new cycle of teachers' lesson preparation and resource curation. Accordingly, I aligned the beginning time in the relational event model with the school cycle, and assumed that in the new preparation cycle, teachers would orient themselves to curate resources in the direction of a different teaching context for a coming school year. Altogether, I assumed that all teachers had an invariant prior activity at the level of zero for resources they were going to curate in the 2016-17 school year. Thus, no further control on teachers' prior curation activity was needed in the relational-event social-influence model.

Model Specification for Testing the Network Exposure Effect

The data capacity allows me to answer five questions—12 hypotheses—around the effect of network influence in teachers' resource curation process. The first and second questions test hypotheses around the main network exposure effects, while the third to fifth focus on the network exposure effect interacting with individuals' attributes, resource curation context, and individuals' perception of teaching.

My first question investigates whether teachers' resource curation is influenced by the direct exposure to network members in egocentric online one-mode networks (see Model 1-1); and if the network influence remains significant after accounting for the resource-mediated social selection in teachers' resource curation in two-mode networks, i.e., including the latent space positions of teachers and resources (see Model 1-2). My second question examines whether teachers are influenced more by online-only peers as compared to school and district colleagues for resource curation on Pinterest (see Model 2). The model degree of freedoms for testing main network exposure effects is around 185,130.

The third question examines whether the network influence differs between teachers at different career stages (see Model 3-1); whether early-career teachers, compared to experienced teachers, are influenced more by school and district colleagues, and also whether early-career teachers are influenced less by online-only peers (see Model 3-2); and if teachers from different grades are influenced differently by the surrounding social context (see Model 3-3). The model degree of freedoms for testing the main and moderating effects of teacher attributes is around 40. Thus, I may have limited degree of freedoms and power to detect and estimate these effects.

Regarding the moderating role of the resource curation context on the network influence effect, I investigate whether teachers are influenced by their networks differently regarding resources of different types (see Model 4-1); and if the network influence varies by the origin of the created resource (see Model 4-2). The model degree of freedoms for testing the main and moderating effects of resource curation context is around 65. Regarding question five, I explore whether teachers are influenced less by their social context if they have an effective teaching disposition (see Model 5-1), or are competent in classroom management (see Model 5-2), or view state test expectations as a supporting factor for them to enact instruction (see Model 5-3); and if teachers are influenced more by their social surroundings when they are in a difficult teaching environment (see Model 5-4).

Building on a relational event model set-up, models below include the *network exposure effect* β_1 as the parameter associated with the social influence hypothesis. From model 1-2 to model 5-4, I accounted for the similarity of latent positions between teachers and resources when estimating both the marginal network exposure effects and the interaction effect of network exposures with other factors. Across different models, I controlled for the linear effect of *week* and teachers' *low and high curation volumes* at the weekly level. Two teacher-related attributes were included to account for the *early career teacher* effect and the non-linear effect of teacher's *grade level taught* (with the lower-elementary grades set as the reference group as compared to the mid-elementary grades and upper-elementary grades). As to the resource-related attributes, the effects of the *resource type* and of the *resource origin* were included. Lastly, the teachers' and resources' fixed effects, α_i and α_j, were added to control for the remaining heterogeneity among teachers for their active engagement in resource curation, as well as resources' attractiveness of inducing curation activities.

Models of Network Exposure Effects

Model 1-1. Network exposure effect without controlling for latent space positions

Logit P(teacher-resource tie_{ijt}=1|teacher-resource tie_{ijs}=0, s<t)= β_0

+ β_1 network $\text{exposure}_{ij(t-1)}$

+ β_2 week_t

+ β_3 low curation volume_t

+ β_4 high curation volume_t

+ β_5 teacher's career stage_i

+ β_6 mid-elementary grade_i

+ β_7 upper-elementary grade_i

+ β_8 classroom management (resource type)$_j$

+ β_9 classroom resource (resource type)$_j$

+ β_{10} social emotional learning (resource type)$_j$

+ β_{11} teacher-to-teacher consumption markets (resource origin)$_j$

+ β_{12} periphery online secondary sites (resource origin)$_j$

+ β_{13} educational organizations (resource origin)$_j$

+ $\Sigma\alpha_i + \Sigma\alpha_j$

Model 1-2. Network exposure effect, controlling for latent space positions

Logit P(teacher-resource tie_{ijt}=1|teacher-resource tie_{ijs}=0, s<t)= β_0

+ β_1 network $\text{exposure}_{ij(t-1)}$

+ β_2 similarity of latent space $\text{positions}_{ij(t1\rightarrow t)}$

$+ \beta_3$ missing indicator on the similarity of latent space positions$_{ij(t1 \rightarrow t)}$

$+ \beta_4$ week$_t$

$+ \beta_5$ low curation volume$_t$

$+ \beta_6$ high curation volume$_t$

$+ \beta_7$ teacher's career stage$_i$

$+ \beta_8$ mid-elementary grade$_i$

$+ \beta_9$ upper-elementary grade$_i$

$+ \beta_{10}$ classroom management (resource type)$_j$

$+ \beta_{11}$ classroom resource (resource type)$_j$

$+ \beta_{12}$ social emotional learning (resource type)$_j$

$+ \beta_{13}$ teacher-to-teacher consumption markets (resource origin)$_j$

$+ \beta_{14}$ periphery online secondary sites (resource origin)$_j$

$+ \beta_{15}$ educational organizations (resource origin)$_j$

$+ \Sigma\alpha_i + \Sigma\alpha_j$

Model 2. Separate network exposure effects from school-and-district colleagues versus online-only peers

Logit P(teacher-resource tie$_{ijt}$=1|teacher-resource tie$_{ijs}$=0, s<t)= β_0

$+ \beta_1$ network exposure to school-and-district colleagues$_{ij(t-1)}$

$+ \beta_2$ network exposure to online-only peers$_{ij(t-1)}$

$+ \beta_3$ similarity of latent space positions$_{ij(t1 \rightarrow t)}$

$+ \beta_4$ missing indicator on the similarity of latent space positions$_{ij(t1 \rightarrow t)}$

$+ \beta_5$ week$_t$

$+ \beta_6$ low curation volume$_t$

+ β_7 high curation volume$_t$

+ β_8 teacher's career stage$_i$

+ β_9 mid-elementary grade$_i$

+ β_{10} upper-elementary grade$_i$

+ β_{11} classroom management (resource type)$_j$

+ β_{12} classroom resource (resource type)$_j$

+ β_{13} social emotional learning (resource type)$_j$

+ β_{14} teacher-to-teacher consumption markets (resource origin)$_j$

+ β_{15} periphery online secondary sites (resource origin)$_j$

+ β_{16} educational organizations (resource origin)$_j$

+ $\Sigma\alpha_i + \Sigma\alpha_j$

Models of Network Exposure Effects Interacting with Individual Attributes

Model 3-1. Network exposure effect interacting with the career stage of teachers

Logit P(teacher-resource tie$_{ijt}$=1|teacher-resource tie$_{ijs}$=0, s<t)= β_0

+ β_1 network exposure$_{ij(t-1)}$

+ β_2 teacher's career stage$_i$

+ β_3 network exposure$_{ij(t-1)}$ × teacher's career stage$_i$

+ β_4 similarity of latent space positions$_{ij(t1\rightarrow t)}$

+ β_5 missing indicator on the similarity of latent space positions$_{ij(t1\rightarrow t)}$

+ …

Note. Model 3-1 controlled for the full covariate set, including *teacher's grade level taught*, *resource type*, *resource origin*, and the fixed effects of *teacher's outdegree* and of *resource's indegree*.

Model 3-2. Separate network exposure effects interacting with the career stage of teachers

Logit P(teacher-resource tie$_{ijt}$=1|teacher-resource tie$_{ijs}$=0, s<t)= β_0

+ β_1 network exposure to school-and-district colleagues$_{ij(t-1)}$

+ β_2 network exposure to online-only peers$_{ij(t-1)}$

+ β_3 teacher's career stage$_i$

+ β_4 network exposure to school-and-district-colleagues$_{ij(t-1)}$ × teacher's career stage$_i$

+ β_5 network exposure to online-only peers$_{ij(t-1)}$ × teacher's career stage$_i$

+ β_6 similarity of latent space positions$_{ij(t1\rightarrow t)}$

+ β_7 missing indicator on the similarity of latent space positions$_{ij(t1\rightarrow t)}$

+ …

Note. Model 3-2 controlled for the full covariate set, including *teacher's grade level taught*, *resource type*, *resource origin*, and the fixed effects of *teacher's outdegree* and of *resource's indegree*.

Model 3-3. Network exposure effect interacting with the grade level taught

Logit P(teacher-resource tie$_{ijt}$=1|teacher-resource tie$_{ijs}$=0, s<t)= β_0

+ β_1 network exposure$_{ij(t-1)}$

+ β_2 mid-elementary grades$_i$

+ β_3 upper-elementary grades$_i$

+ β_4 network exposure$_{ij(t-1)}$ × mid-elementary grades$_i$

+ β_5 network exposure$_{ij(t-1)}$ × upper-elementary grades$_i$

+ β_6 similarity of latent space positions$_{ij(t1\rightarrow t)}$

+ β_7 missing indicator on the similarity of latent space positions$_{ij(t1\rightarrow t)}$

+ …

Note. Model 3-3 controlled for the full covariate set, including *teacher's career stage*, *resource type*, *resource origin*, and the fixed effects of *teacher's outdegree* and of *resource's indegree*.

Models of Network Exposure Effects Interacting with the Resource Curation Context

Model 4-1. Network exposure effect interacting with the types of resources

Logit P(teacher-resource tie_{ijt}=1|teacher-resource tie_{ijs}=0, s<t)= β_0

+ β_1 network $\text{exposure}_{ij(t-1)}$

+ β_2 classroom management (resource $\text{type})_j$

+ β_3 classroom resource (resource $\text{type})_j$

+ β_4 social emotional learning (resource $\text{type})_j$

+ β_5 network $\text{exposure}_{ij(t-1)}$ × classroom management (resource $\text{type})_j$

+ β_6 network $\text{exposure}_{ij(t-1)}$ × classroom resource (resource $\text{type})_j$

+ β_7 network $\text{exposure}_{ij(t-1)}$ × social emotional learning (resource $\text{type})_j$

+ β_8 similarity of latent space $\text{positions}_{ij(t1\rightarrow t)}$

+ β_9 missing indicator on the similarity of latent space $\text{positions}_{ij(t1\rightarrow t)}$

+ …

Note. Model 4-1 controlled for the full covariate set, including *teacher's career stage*, *teacher's grade level taught*, *resource type*, and the fixed effects of *teacher's outdegree* and of *resource's indegree*.

Model 4-2. Network exposure effect interacting with the origins of resources

Logit P(teacher-resource tie_{ijt}=1|teacher-resource tie_{ijs}=0, s<t)= β_0

+ β_1 network $\text{exposure}_{ij(t-1)}$

+ β_2 teacher-to-teacher consumption markets (resource $\text{origin})_j$

+ β_3 periphery online secondary sites (resource $\text{origin})_j$

$+ \beta_4$ educational organizations (resource origin)$_j$

$+ \beta_5$ network exposure$_{ij(t-1)}$ × teacher-to-teacher consumption markets (resource origin)$_j$

$+ \beta_6$ network exposure$_{ij(t-1)}$ × periphery online secondary sites (resource origin)$_j$

$+ \beta_7$ network exposure$_{ij(t-1)}$ × educational organizations (resource origin)$_j$

$+ \beta_8$ similarity of latent space positions$_{ij(t1 \rightarrow t)}$

$+ \beta_9$ missing indicator on the similarity of latent space positions$_{ij(t1 \rightarrow t)}$

$+ \ldots$

Note. Model 4-2 controlled for the full covariate set, including *teacher's career stage*, *teacher's grade level taught*, *resource origin*, and the fixed effects of *teacher's outdegree* and of *resource's indegree*.

Models of Network Exposure Effects Interacting with Individuals' Perceptions of Teaching

Model 5-1. Network exposure effect interacting with effective teaching disposition

Logit P(teacher-resource tie$_{ijt}$=1|teacher-resource tie$_{ijs}$=0, s<t)= β_0

$+ \beta_1$ network exposure$_{ij(t-1)}$

$+ \beta_2$ early career teacher$_i$

$+ \beta_3$ network exposure$_{ij(t-1)}$ × effective teaching disposition$_i$

$+ \beta_4$ similarity of latent space positions$_{ij(t1 \rightarrow t)}$

$+ \beta_5$ missing indicator on the similarity of latent space positions$_{ij(t1 \rightarrow t)}$

$+ \ldots$

Note. Model 5-1 controlled for the full covariate set, including *teacher's career stage*, *teacher's grade level taught*, *resource type*, *resource origin*, and the fixed effects of *teacher's outdegree* and of *resource's indegree*.

Model 5-2. Network exposure effect interacting with competency in classroom management

Logit P(teacher-resource tie_{ijt}=1|teacher-resource tie_{ijs}=0, s<t)= β_0

+ β_1 network $\text{exposure}_{ij(t-1)}$

+ β_2 early career teacher_i

+ β_3 network $\text{exposure}_{ij(t-1)}$ × competency in classroom management_i

+ β_4 similarity of latent space $\text{positions}_{ij(t1\rightarrow t)}$

+ β_5 missing indicator on the similarity of latent space $\text{positions}_{ij(t1\rightarrow t)}$

+ …

Note. Model 5-2 controlled for the full covariate set, including *teacher's career stage*, *teacher's grade level taught*, *resource type*, *resource origin*, and the fixed effects of *teacher's outdegree* and of *resource's indegree*.

Model 5-3. Network exposure effect interacting with perceived helpfulness of state test expectations

Logit P(teacher-resource tie_{ijt}=1|teacher-resource tie_{ijs}=0, s<t)= β_0

+ β_1 network $\text{exposure}_{ij(t-1)}$

+ β_2 early career teacher_i

+ β_3 network $\text{exposure}_{ij(t-1)}$ × perceived helpfulness of state test expectations_i

+ β_4 similarity of latent space $\text{positions}_{ij(t1\rightarrow t)}$

+ β_5 missing indicator on the similarity of latent space $\text{positions}_{ij(t1\rightarrow t)}$

+ …

Note. Model 5-3 controlled for the full covariate set, including *teacher's career stage*, *teacher's grade level taught*, *resource type*, *resource origin*, and the fixed effects of *teacher's outdegree* and of *resource's indegree*.

Model 5-4. Network exposure effect interacting with pervasive beliefs among teachers that students aren't motivated to learn

Logit P(teacher-resource tie_{ijt}=1|teacher-resource tie_{ijs}=0, s<t)= β_0

+ β_1 network $\text{exposure}_{ij(t-1)}$

+ β_2 early career teacher_i

+ β_3 network $\text{exposure}_{ij(t-1)}$ × school teachers' beliefs that students aren't motivated to learn_i

+ β_4 similarity of latent space $\text{positions}_{ij(t1\rightarrow t)}$

+ β_5 missing indicator on the similarity of latent space $\text{positions}_{ij(t1\rightarrow t)}$

+ …

Note. Model 5-4 controlled for the full covariate set, including *teacher's career stage*, *teacher's grade level taught*, *resource type*, *resource origin*, and the fixed effects of *teacher's outdegree* and of *resource's indegree*.

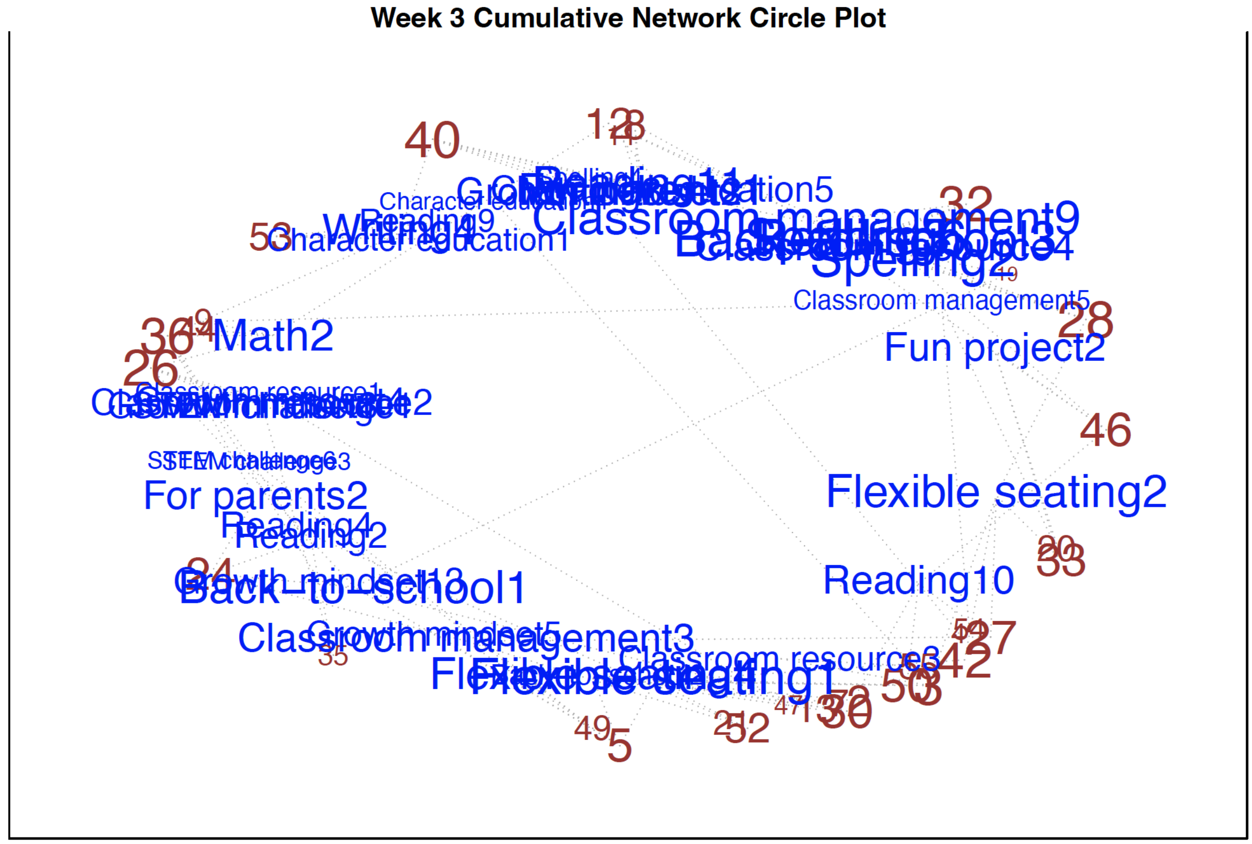
RESULTS

Visualization of Latent Space Positions

To visualize the latent space positions of teachers and resources, I used the circle plot function in AMEN package (Hoff, 2018), which describes the latent factors of a rank-2 model (Figure 10). Teachers as senders, and resources as receivers, are plotted in red and blue respectively (Figure 16). The directions of teachers' vectors are plotted in red, with teachers labeled in numbers; while directions of resources' vectors are plotted in blue, with resources labeled by their category. The size of the labels indicates the magnitude of teachers' and resources' vectors. Dotted lines represent a greater than expected resource curation tie based on the baseline density and senders' and receivers' (i.e., row and column) additive effects. For example, *teacher*-36 and *math*-2 at the left are vectors with large magnitudes pointing toward a similar direction, based on a rank-2 factor model of the cumulative, weekly teacher-resource two-mode network at week three. Thus, they have similar factor scores and are plotted close in the latent space. The similarities of teachers' and resources' vectors were entered into the relational event model as a control to account for the two-mode network dependencies. See Appendix C for the cumulative, weekly circle plot for each of the 48 weeks.

Figure 16

Circle Plot of the Latent Space Positions of Teachers and Resources in the Cumulative, Weekly Network at Week Three



MCMC Diagnostics

I examined the MCMC diagnostics of the two-dimensional latent space model estimations to evaluate their Bayesian model fit. Figure 17 and Figure 18 are examples of the MCMC diagnostics of the cumulative, weekly network at week 47. First, the autocorrelation plot showed that the correlation between every sample and its *k*-lag goes down quickly, thus can be considered independent, indicating that the chain has a quick mixing. Second, the sign of trace plots walking across the parameter space indicates that the MCMC sampler mixes well and converges. I will not present the remaining MCMC diagnostics plots for the estimations of other cumulative, weekly networks here, as they produced similar diagnostics plots. With the estimated latent positions, I converted them as the vector similarity for each pair of teachers and resources and included them in the final regression for the relational event model of teachers' resource curation. Here, I won't further interpret the posterior density of latent position estimates along each individual dimension, as they are not the interest of this dissertation—only their positions in the two-dimensional space are the focus.

Figure 17

The Autocorrelation Plot of the Latent Space Model Estimation of the Cumulative, Weekly Network at Week 47

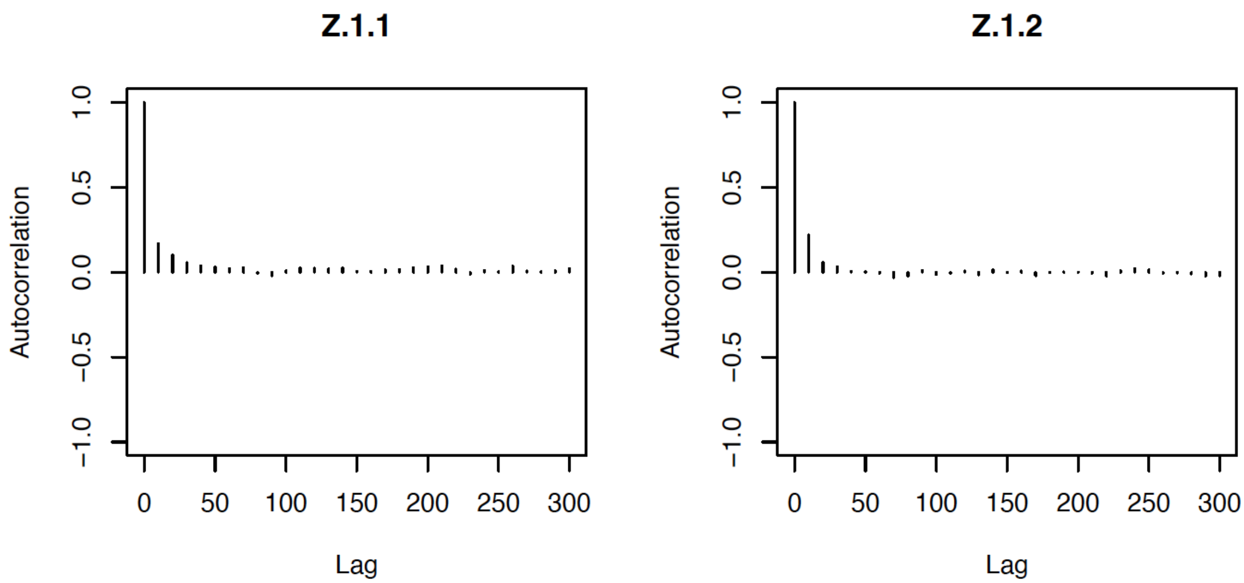
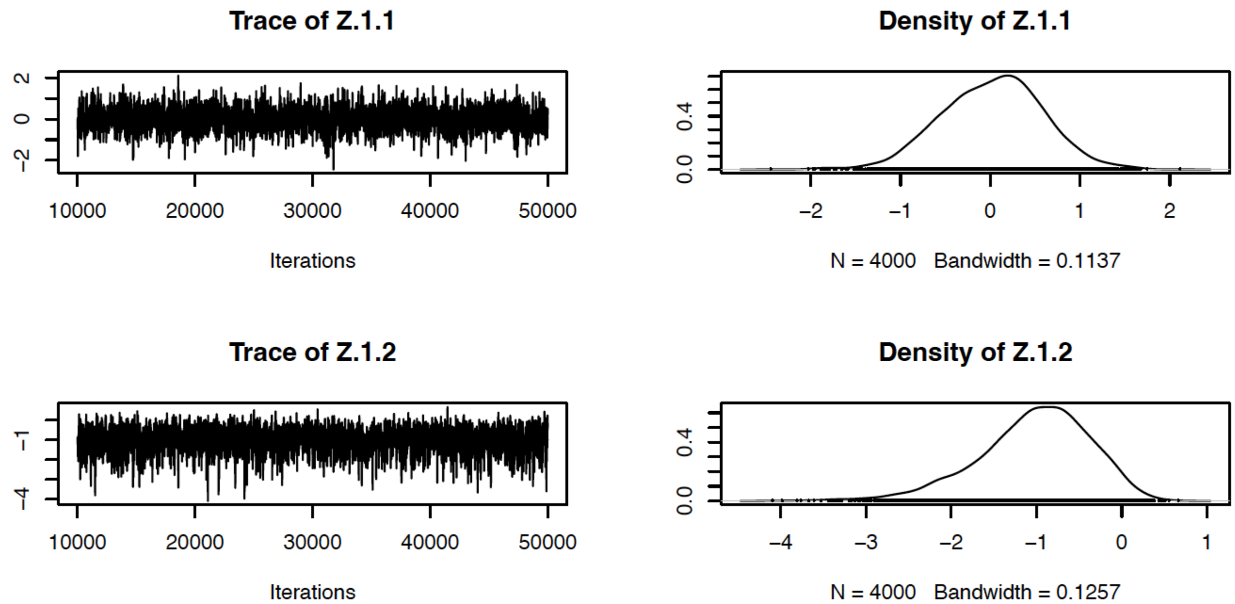


Figure 18
The Trace Plot of the Latent Space Model Estimation of the Cumulative, Weekly Network at Week 47



Variances of Teachers and Resources

Before estimating the network exposure effect, I used the software *HLM 8* to fit an intercept-only cross-classified random effect model (i.e., the baseline model) to estimate the variance in teachers' resource curation activities (i.e., teachers' outdegree) and the variance in resources being curated (i.e., resources' indegree) (Figure 10). However, the model did not converge with the penalized quasi-likelihood estimation method in *HLM*, which posed an issue for further relying on the random effect specification for estimating the full network exposure model. Nonetheless, findings indicated that the estimated variance component associated with teachers' resource curation activities (i.e., row variance) was significant ($\sigma^2_{\text{teacher outdegree}}$=0.865, p<.0001). In contrast, though significant, the variance component associated with resources being curated (i.e., column variance) was small ($\sigma^2_{\text{resource indegree}}$=0.002, p=.015). In other words, there was a large variance in teachers' resource curation activities, compared to a small variance in resources being curated.

This result was consistent with the network statistics of sender and receiver heterogeneity reported in Table 2. Specifically, the standard deviation of the 55 teachers' curated resource proportion was 0.0988, while the standard deviation of the 81 resources being curated by a proportion of teachers was 0.0308. To explore the impact of truncating resources by their in-degree (i.e., at least four teachers curating) on the variance of resources, I compared the resource in-degree distribution before and after the truncation. Results indicated that before the truncation, there were 5,169 resources, with the resource in-degree mean of 1.20 and a standard deviation of 0.67. After the truncation, there were 81 resources, with the in-degree mean of 5.07 and a standard deviation of 1.69. This indicated that before the truncation, a majority of resources had only been curated by one teacher, as 87.04 percent of the resources had an in-degree of one. The comparison displayed an even narrower in-degree variance before the truncation.

Therefore, though the resource variance was smaller than the teacher variance, truncating the resource in-degree distribution increased the resource variance. This may suggest that the number of times a resource was curated followed a power law distribution, in which a few resources closer to the top of the in-degrees captured more variances than a majority of resources at the bottom of the in-degrees. In fact, Pinterest reported 444 million monthly average users and 330 billion saved pins in 2022, which grew from 300 million users and 200 billion pins in 2019 (Pinterest Labs, 2022). As pins outnumbered users, the pins' in-degree would follow a more extreme power law distribution, with a tremendous amount of pins only being curated by one user. This is a sign of little variance observed in the pins' in-degree compared to the users' outdegree distribution, which may also follow a power law distribution but in a less extreme fashion. This may explain why the resource variance was smaller than the teacher variance.

I controlled for the effects of teachers' outdegree and resources' indegree in the final model. I compared the baseline model with random effects (*melogit* command in *STATA* with the LaPlace approximation) to that model with fixed effects (*STATA logit* command) regarding teachers' outdegree and resources' indegree (Figure 10). The log-likelihood indicated that the fixed effects model (with a log likelihood of -2670.45) performed better than the random effects model (with a log likelihood of -2721.12). Nevertheless, after penalizing the model complexity, the random effects model had a lower Bayesian Information Criterion (BIC) of 5478.62, thereby a better model, compared to the fixed effects model (BIC=5656.26). However, the random effects model did not converge after adding in predictors and all the covariates. Only when the teacher or the resource random effect was included one at a time did the full model run. Therefore, I chose to use the fixed effects model, with both teachers and resources fixed effects, to estimate the network exposure effect in the following regression models. The *logit* command in the software *STATA* was used for the estimation (Figure 10).

Regression Results

Network Exposure Effects

Findings indicate a positive relationship between teachers' online network exposures and the hazard of their resource curation before controlling for the latent space positions of teachers and resources (β=0.084, *se*=0.022, Model 1-1 in Table 5). For each time their network members curated a resource in the prior week, the odds of teachers' hazard of resource curation increased by 8.76 percent in the following week. Furthermore, the network exposure effect remained significant after accounting for the latent space positions of teachers and resources in the two-mode networks (β=0.082, *se*=0.024, Model 1-2 in Table 5), though the size of the network exposure effect shrank by 2.72 percent. The finding is robust as 42.21 percent of the estimated network exposure effect would have to be due to bias to invalidate the statistical inference. Also, the estimated effect of similarities of teachers and resources as vectors in the latent space was significant (β=1.632, *se*=0.077, Model 1-2 in Table 5).

Table 5

Regression Analyses for the Network Exposure Effects (N = 161,054)

Independent variable	Model 1-1 B (SE B)	Model 1-1 Odds Ratio (e^B)	Model 1-2 B (SE B)	Model 1-2 Odds Ratio (e^B)	Model 2 B (SE B)	Model 2 Odds Ratio (e^B)
Network exposure (overall)	0.084*** (0.022)	1.088	0.082** (0.024)	1.085		
Network exposure to school-and-district colleagues					0.150 (0.269)	1.162
Network exposure to online-only peers					0.082** (0.024)	1.085
Similarity of teachers' and resources' latent positions (vectors' inner product)			1.632*** (0.077)	5.114	1.631*** (0.077)	5.109
Missing indicator for the similarity of latent positions			-0.806 (0.733)	0.447	-0.805 (0.733)	0.447
Week	-0.020*** (0.005)	0.980	-0.059*** (0.005)	0.943	-0.059*** (0.005)	0.943
Low curation volume indicator	-1.316*** (0.314)	0.268	-1.161*** (0.317)	0.313	-1.162*** (0.317)	0.313
High curation volume indicator	1.018*** (0.122)	2.768	1.277*** (0.123)	3.586	1.276*** (0.123)	3.582
Teachers in early career stage	-0.009 (0.188)	0.991	-0.033 (0.199)	0.968	-0.031 (0.199)	0.969
Grade (*Lower-elementary* as reference group)						
Mid-elementary	0.040 (0.249)	1.041	0.228 (0.237)	1.256	0.229 (0.237)	1.257
Upper-elementary	0.013 (0.290)	1.013	-0.078 (0.293)	0.925	-0.078 (0.293)	0.925
Resource type (*Subject-specific* as reference group)						
Classroom management	-0.098 (0.201)	0.907	0.303 (0.205)	1.354	0.302 (0.205)	1.353
Classroom resource	-0.088 (0.162)	0.916	-0.014 (0.171)	0.986	-0.015 (0.171)	0.985

Table 5 (cont'd)

Social & emotional learning	-0.123 (0.157)	0.884	0.142 (0.161)	1.153	0.142 (0.161)	1.153
Resource origin (*Educator's blogs* as reference group)						
Educational organizations	0.014 (0.213)	1.014	-0.103 (0.227)	0.902	-0.100 (0.227)	0.905
Periphery online secondary sites	0.154 (0.290)	1.166	-0.332 (0.308)	0.717	-0.330 (0.308)	0.719
Teacher-to-teacher consumption markets	-0.014 (0.248)	0.986	-0.101 (0.256)	0.904	-0.098 (0.256)	0.907
Log-likelihood (Goodness-of-fit)	-2272.074		-1857.021		-1856.989	

Note. B is the estimated effect in log-odds unit; SE B is the standard error of B; Odds Ratio (e^B) is the estimated effect in odds unit.
*p < .05. **p < .01. ***p < .001.

When I split the network exposures based on whether the alters were the school-and-district colleagues or online-only peers, I found that the network exposure effect from school-and-district colleagues was not statistically significant (β=0.150, *se*=0.269, Model 2 in Table 5). In contrast, that effect from online-only peers was positive in predicting teachers' hazard of curation. Specifically, exposure to online-only peers' curated resources increased the odds of teachers' hazard of curation by 8.55 percent (β=0.082, *se*=0.024, Model 2 in Table 5). Nevertheless, the coefficient of the network exposure effect from school-and-district colleagues was larger than the coefficient from online-only peers. This non-significant result was due to a larger standard error associated with the network exposure effect from school-and-district colleagues, which was caused by teachers connected with fewer school-and-district colleagues in their online networks compared to a large number of connections with online-only peers.

Beyond the network exposure effects, results disclosed a negative linear week effect (β=-0.059, *se*=0.005, Model 1-2 in Table 5). Specifically, there was a 5.73 percent decrease in the odds of teachers' resource curation for each additional week into the school year. Extreme curation weeks significantly predicted teachers' curation activities, as the odds of teachers' curation in low curation weeks were 0.31 times lower compared to regular weeks (β=-1.161, *se*=0.317, Model 1-2 in Table 5), and the odds of teachers' hazard of curation in high curation weeks were 3.58 times higher (β=1.277, *se*=0.123, Model 1-2 in Table 5). Apart from the significant findings, teachers' resource curation activities differed by neither individuals' attributes (i.e., career stage and the grade level taught), nor the resources' characteristics (i.e., resource type and resource origin). I further removed the teachers' and resources' fixed effects and refit the model to test for effects of individual attributes and of resource characteristics. Results remained the same with the exception of a significant negative effect of upper-elementary grades (β=-0.532, *se*=0.226) on the hazard of teachers' resource curation, as compared to lower-elementary grades.

Moderating Effects of Individual Attributes on Network Exposures

The network exposure effect can be moderated by individuals' attributes. I found a negative interaction effect between the network exposures and teachers in early career stages (β=-0.138, *se*=0.046, Model 3-1 in Table 6). The network exposure effect of early career teachers was 12.89 percent lower in odds-ratio units, compared to experienced teachers. In other words, early career teachers were influenced less by network members' curation activity, compared to experienced teachers. Further investigations showed that the career stage did not moderate the effect of network exposures from school-and-district colleagues (β=-0.012, *se*=0.636, Model 3-2 in Table 6), but the career stage significantly moderated the network exposure effect from online-only peers (β=-0.139, *se*=0.046, Model 3-2 in Table 6). For early career teachers, their network exposure effect from online-only peers was 12.98 percent lower in odds-ratio units, compared to their experienced counterparts. That is, compared with the experienced teachers, early career teachers were equally unresponsive to the network influence from school-and-district colleagues on Pinterest; nevertheless, early career teachers were significantly less influenced by the resource curation activity of online-only peers.

Table 6

Regression Analyses for the Interaction Effects of Network Exposure and Teachers' Early Career Stage (N = 161,054)

Independent variable	Model 3-1 B (SE B)	Model 3-1 Odds Ratio (e^B)	Model 3-2 B (SE B)	Model 3-2 Odds Ratio (e^B)
Network exposure (overall)	0.190*** (0.033)	1.209		
Teachers in early career stage	-0.0003 (0.200)	1.000	-0.004 (0.201)	0.996
Interaction between network exposure and early career stage	-0.138** (0.046)	0.871		
Network exposure to school-and-district colleagues			0.147 (0.305)	1.158
Interaction between network exposure to school-and-district colleagues and early career stage			-0.012 (0.636)	0.988
Network exposure to online-only peers			0.191*** (0.033)	1.210
Interaction between network exposure to online-only peers and early career stage			-0.139** (0.046)	0.870
Similarity of teachers' and resources' latent positions (vectors' inner product)	1.641*** (0.077)	5.160	1.641*** (0.078)	5.160
Missing indicator for the similarity of latent positions	-0.798 (0.733)	0.450	-0.799 (0.734)	0.450
Week	-0.059*** (0.005)	0.943	-0.059*** (0.005)	0.943
Low curation volume indicator	-1.166*** (0.317)	0.312	-1.165*** (0.317)	0.312
High curation volume indicator	1.275*** (0.123)	3.579	1.275*** (0.123)	3.579
Grade (*Lower-elementary* as reference group)				
Mid-elementary	0.268 (0.238)	1.307	0.271 (0.239)	1.311
Upper-elementary	-0.104 (0.295)	0.901	-0.102 (0.295)	0.903
Resource type (*Subject-specific* as reference group)				
Classroom management	0.305 (0.206)	1.357	0.305 (0.206)	1.357
Classroom resource	-0.017 (0.171)	0.983	-0.017 (0.171)	0.983
Social & emotional learning	0.147 (0.161)	1.158	0.147 (0.161)	1.158
Resource origin (*Educator's blogs* as reference group)				
Educational organizations	-0.096 (0.227)	0.908	-0.097 (0.227)	0.908
Periphery online secondary sites	-0.325 (0.307)	0.723	-0.327 (0.308)	0.721
Teacher-to-teacher consumption markets	-0.098 (0.256)	0.907	-0.099 (0.256)	0.906
Log-likelihood (Goodness-of-fit)	-1853.649		-1853.628	

Note. B is the estimated effect in log-odds unit; SE B is the standard error of B; Odds Ratio (e^B) is the estimated effect in odds unit.

Table 6 (cont'd)
*p < .05. **p < .01. ***p < .001.

Regarding the moderating effect of teachers' grade level taught, results displayed a significant and positive interaction effect between the network exposures and teachers from the mid-elementary grades, compared with teachers from the lower-elementary grades (β=0.384, *se*=0.190, Model 3-3 in Table 7). Teachers in mid-elementary grades were influenced more by the resource curation activity of their network members. There was no systematic difference of the network exposure effect between upper-elementary and lower-elementary grade teachers.

Table 7

Regression Analysis for the Interaction Effects of Network Exposure and Grade Level Taught (N = 161,054)

	Model 3-3	
Independent variable	B (SE B)	Odds Ratio (e^B)
Network exposure (overall)	0.083** (0.025)	1.087
Grade (*Lower-elementary* as reference group)		
Mid-elementary	0.167 (0.239)	1.182
Upper-elementary	0.003 (0.295)	1.003
Interaction between network exposure with mid-elementary grades	0.384* (0.190)	1.468
Interaction between network exposure with upper-elementary grades	-0.390 (0.351)	0.677
Similarity of teachers' and resources' latent positions (vectors' inner product)	1.637*** (0.077)	5.140
Missing indicator for the similarity of latent positions	-0.801 (0.733)	0.449
Week	-0.059*** (0.005)	0.943
Low curation volume indicator	-1.158*** (0.317)	0.314
High curation volume indicator	1.278*** (0.123)	3.589
Teachers in early career stage	-0.068 (0.199)	0.934
Resource type (*Subject-specific* as reference group)		
Classroom management	0.297 (0.206)	1.346
Classroom resource	-0.014 (0.171)	0.986
Social & emotional learning	0.141 (0.161)	1.151
Resource origin (*Educator's blogs* as reference group)		
Educational organizations	-0.089 (0.227)	0.915
Periphery online secondary sites	-0.326 (0.308)	0.722
Teacher-to-teacher consumption markets	-0.083 (0.256)	0.920
Log-likelihood (Goodness-of-fit)	-1854.170	

Note. B is the estimated effect in log-odds unit; SE B is the standard error of B; Odds Ratio (e^B) is the estimated effect in odds unit.

*p < .05. **p < .01. ***p < .001.

Moderating Effects of Resource Curation Context on Network Exposures

Resource curation context also plays a moderating role on the effect of network exposures from members in teachers' online networks. I found a significant positive interaction effect between network exposures and Classroom Resources (i.e., facilitating materials), as compared to the effect of network exposures around Subject-Specific resources (β=0.310, *se*=0.102, Model 4-1 in Table 8). That is, teachers were more influenced by their online networks around facilitating Classroom Resources. The odds of teachers' curation hazard were increased by 36.34 percent when they were exposed to facilitating Classroom Resources in their online networks, as compared to their network exposure effect to Subject-Specific resources. At the borderline significance level, teachers' network exposure effect around Social and Emotional Learning resources was higher than that effect around Subject-Specific resources (β=0.250, *se*=0.147, Model 4-1 in Table 8). No systematic difference was found surrounding the moderating effect between Classroom Management resources and Subject-Specific resources.

Table 8

Regression Analyses for the Interaction Effects of Network Exposure and the Resource Curation Context (N = 161,054)

Independent variable	Model 4-1		Model 4-2	
	B (SE B)	Odds Ratio (e^B)	B (SE B)	Odds Ratio (e^B)
Network exposure (overall)	0.076** (0.028)	1.079	0.077** (0.025)	1.080
Resource type (*Subject-specific* as reference group)				
Classroom management	-0.135 (0.161)	0.874	0.304 (0.205)	1.355
Classroom resource	0.102 (0.189)	1.107	-0.011 (0.171)	0.989
Social & emotional learning	-0.189 (0.160)	0.828	0.145 (0.161)	1.156
Interaction between network exposure and classroom management resources	-0.042 (0.080)	0.959		
Interaction between network exposure and facilitating classroom resources	0.310** (0.102)	1.363		
Interaction between network exposure and social & emotional learning resources	0.250+ (0.147)	1.284		
Resource origin (*Educator's blogs* as reference group)				
Educational organizations	-0.089 (0.228)	0.915	0.057 (0.234)	1.059
Periphery online secondary sites	-0.317 (0.309)	0.728	-0.346 (0.244)	0.708
Teacher-to-teacher consumption markets	-0.080 (0.257)	0.923	-0.012 (0.166)	0.988
Interaction between network exposure and resources from educational organizations			0.189 (0.188)	1.208
Interaction between network exposure and resources from periphery online secondary sites			0.665* (0.265)	1.944
Interaction between network exposure and resources from teacher-to-teacher consumption markets			0.116 (0.294)	1.123
Similarity of teachers' and resources' latent positions (vectors' inner product)	1.628*** (0.077)	5.094	1.631*** (0.077)	5.109
Missing indicator for the similarity of latent positions	-0.801 (0.733)	0.449	-0.802 (0.733)	0.448
Week	-0.058*** (0.005)	0.944	-0.059*** (0.005)	0.943
Low curation volume indicator	-1.164*** (0.317)	0.312	-1.161*** (0.317)	0.313
High curation volume indicator	1.280*** (0.123)	3.597	1.272*** (0.123)	3.568
Teachers in early career stage	-0.003 (0.200)	0.997	-0.018 (0.200)	0.982

Table 8 (cont'd)

Grade (*Lower-elementary* as reference group)				
Mid-elementary	0.251 (0.237)	1.285	0.246 (0.237)	1.279
Upper-elementary	-0.135 (0.298)	0.874	-0.098 (0.295)	0.907
Log-likelihood (Goodness-of-fit)	-1853.02		-1854.690	

Note. B is the estimated effect in log-odds unit; SE B is the standard error of B; Odds Ratio (e^B) is the estimated effect in odds unit.
+p < .1. *p < .05. **p < .01. ***p < .001.

In regard to the moderating effect of the resource origin, I found a significant and positive interaction effect between teachers' network exposures and resources from Periphery Online Secondary Sites, compared to that effect around resources from Educator's Blogs (β=0.665, *se*=0.265, Model 4-2 in Table 8). In other words, teachers were more influenced by online networks surrounding resources from Periphery Online Secondary Sites. Specifically, the odds of teachers' hazard of resource curation were increased by 94.45 percent if they were exposed to members in online networks who curated resources from Periphery Online Secondary Sites. There was no significant difference in the moderating effect among resources that originated from Educator's Blogs, Teacher-To-Teacher Consumption Markets, and Educational Organizations.

Secondary Analyses on the Moderating Role of Teachers' Perceptions of Teaching on Network Exposure Effects

As exploratory analyses of the moderating role of teachers' perception of teaching, I have tested 17 survey items on teachers' perceptions and reported the significant findings with adjusted alpha for testing multiple hypotheses. I found a negative interaction effect between the network exposures and teachers' effective teaching disposition at the borderline significance level (β=-0.354, *se*=0.211, Model 5-1 in Table 9). Teachers who held an effective teaching disposition were influenced less by the resource curation activity in their online networks. In addition, there was a positive interaction effect between teachers' network exposures and their perceived competency in classroom management (β=0.707, *se*=0.269, Model 5-2 in Table 9). Teachers who perceived themselves competent in classroom management were influenced more by their online networks. Also, results indicated that the perceived helpfulness of state test expectations positively interacted with the network exposure effect (β=0.353, *se*=0.117, adjusted

p=.027, Model 5-3 in Table 9). Teachers who perceived the state test expectations as helpful were influenced more by their online networks. Lastly, the finding reveals that pervasive beliefs among school teachers of students being not motivated to learn positively moderated the effect of network exposures (β=0.231, *se*=0.082, adjusted p=.024, Model 5-4 in Table 9). Teachers who were in a school with pervasive teacher beliefs that students were not motivated to learn were influenced more by their online networks. In summary, mixed results have been found around the moderating effects of teachers' perceptions of teaching on the network exposure effect, with both competent teachers and teachers in difficult situations being more influenced by their online networks.

Table 9

Regression Analyses for the Interaction Effects of Network Exposure and Teachers' Perceptions of Teaching

	Model 5-1	Model 5-2	Model 5-3	Model 5-4
Independent variable	B (SE B)	B (SE B)	B (SE B)	B (SE B)
Network exposure (overall)	1.121+ (0.631)	-2.064* (0.809)	-0.996** (0.358)	-0.177+ (0.094)
Effective teaching disposition	-0.148 (0.249)			
Interaction between network exposure and effective teaching disposition	-0.354+ (0.211)			
Competency in classroom management		-0.550+ (0.288)		
Interaction between network exposure and competency in classroom management		0.707** (0.269)		
Perceived helpfulness of state test expectations			0.170 (0.135)	
Interaction between network exposure and perceived helpfulness of state test expectations			0.353* (0.117)	
Pervasive beliefs among teachers that students aren't motivated to learn				-0.109 (0.119)
Interaction between network exposure and pervasive beliefs among teachers that students aren't motivated to learn				0.231* (0.082)
Similarity of teachers' and resources' latent positions (vectors' inner product)	1.586*** (0.084)	1.604 (0.085)	1.600*** (0.085)	1.617*** (0.086)
Missing indicator for the similarity of latent positions	-0.809 (0.739)	-0.762 (0.741)	-0.807 (0.741)	-1.384 (1.024)
Week	-0.058*** (0.006)	-0.058 (0.006)	-0.059*** (0.006)	-0.062*** (0.006)
Low curation volume indicator	-1.260*** (0.349)	-1.372 (0.368)	-1.214** (0.349)	-1.183** (0.350)
High curation volume indicator	1.334*** (0.132)	1.335 (0.133)	1.370*** (0.134)	1.350*** (0.136)
Teachers in early career stage	-0.708* (0.331)	-0.971* (0.413)	-0.534 (0.332)	-0.622 (0.378)
Grade (*Lower-elementary* as reference group)				
Mid-elementary	0.285 (0.328)	0.440 (0.349)	0.363 (0.337)	0.321 (0.389)
Upper-elementary	-0.249 (0.383)	-0.075 (0.360)	-0.253 (0.364)	0.114 (0.425)
Resource type (*Subject-specific* as reference group)				
Classroom management	0.196 (0.220)	0.215 (0.221)	0.140 (0.225)	0.189 (0.226)

Table 9 (cont'd)

Classroom resource	-0.061 (0.180)	-0.086 (0.182)	-0.073 (0.181)	-0.077 (0.183)
Social & emotional learning	-0.046 (0.171)	-0.045 (0.172)	-0.071 (0.172)	-0.106 (0.175)
Resource origin (*Educator's blogs* as reference group)				
Educational organizations	0.106 (0.257)	0.173 (0.263)	0.098 (0.258)	0.145 (0.265)
Periphery online secondary sites	-0.116 (0.343)	-0.085 (0.350)	-0.096 (0.345)	-0.121 (0.353)
Teacher-to-teacher consumption markets	0.110 (0.284)	0.192 (0.290)	0.128 (0.285)	0.171 (0.292)
Log-likelihood (Goodness-of-fit)	-1582.213	-1557.546	-1537.519	-2114.142
N observations	126,964	123,447	123,534	112,860

Note. B is the estimated effect in log-odds unit; SE B is the standard error of B.
+p < .1. *p < .05. **p < .01. ***p < .001.

CONCLUSION AND DISCUSSION

Resource curation on Pinterest serves as a channel for teachers to find professional support and seek information based on their own professional needs, which leverages the collective efforts of the teaching profession in creating and pooling resources from various sources (Torphy et al., 2020). In addition, teachers further utilize online social networks to narrow down specific professionals who they find helpful and relevant in sharing resources that fit their instructional needs (Frank et al., 2020; Penuel et al., 2009). In other words, teachers decide whom they follow online and accordingly establish their online networks to seek resources and continue professional learning. The personal network of a teacher becomes their immediate social context online. Moreover, as more teachers begin to use Pinterest for resource seeking, colleagues from the same district may encounter one another within the online resource space, directly connected or not (Vu et al., 2015). In this situation, online resources function as a social event to bridge teachers from the same district, which creates a second layer of an indirect social context, somewhat salient to teachers who worked in the same local area, jointly served the same geographical student population, and shared similar collective goals of teaching.

This dissertation found that teachers from the Waters school district were influenced by the resource curation activity of members in their direct online networks, i.e., the first layer of their social context. This result supports the social influence hypothesis that teachers' resource curation activity was subject to change when they observed someone in their online networks actively curating resources. Due to a reduced concern for teachers under normative pressure on Pinterest, a significant network exposure effect can be interpreted as teachers choosing to be influenced by their network members to maximize their efforts in resource curation (Coleman, 1988). In other words, teachers establish their own personal professional learning community and learn from others in their networks with respect to ideas, content, and materials that can be used in their classroom (Frank et al., 2004).

As teachers are embedded in two layers of social context during their resource curation on Pinterest, it is crucial to parse out how teachers' resource curation is affected by the indirect district-wide social context of teachers' curation activities and reinvestigate the network influence from teachers' direct online networks. This dissertation finds that the network influence from teachers' immediate social context remained significant, after accounting for the potential resource-mediated social selection process that happened in teachers' indirect district-wide social context. Though Waters school district teachers may have encountered colleagues from the same district in various online social learning events (i.e., under each of the online resources), and may have subsequently followed and curated resources in a similar fashion, teachers' resource curation continued to be influenced by people they followed in their online networks.

The significant similarity effect of teachers and resources in the latent space is aligned with the proposed technique used in latent space models—factor scores of teachers and resources were extracted from the observed sociomatrix decomposition and captured the variances in teachers' and resources' connections in the two-mode network along the two biggest latent space dimensions (Hoff et al., 2002; Hoff, 2018). Teachers' and resources' latent positions attempted to capture complex network dependencies accumulated across the process of teachers' online resource curation over time, and a significant similarity effect manifested that one teacher's curation of a resource was not independent from another teacher's curation of a resource in the two-mode network. Dependencies in teachers' resource curation activities are often an indicative sign of clusters of teachers curating similar resources. Given that Pinterest (2022) developed their recommender algorithm to personalize and suggest similar resources based on what teachers curated previously and also recommend teachers to follow people who pinned similar resources, the significant similarity effect could be capturing part of the clustering phenomenon induced by the Pinterest recommender system, along with teachers' genuine inclinations of curating similar resources and following people with similar curation tastes.

In addition, the social influence effect from the immediate online social context has little overlap with the dependencies among teachers' resource curation in the indirect district-wide social context. Regardless of the two layers of network embeddedness of teachers on Pinterest, the two may not function under the same mechanism, and each social context plays a different role in influencing teachers' resource curation. The formation of teachers' one-mode networks of online resource curation may be motivated by teachers looking for someone who shared resources they have not been exposed to and can be a support for their ongoing professional learning (Coleman, 1988; Frank et al., 2004). In contrast, the formation of teachers' two-mode networks may be driven by teachers with similar teaching predispositions and resource preferences gathered under a resource space with possibilities of being connected and influenced in future rounds of curation activities (Snijders et al., 2013; Fujimoto et al., 2018). Therefore, the immediate social context bestows teachers the opportunities of novel resources, while the indirect social context provides teachers resources that are aligned with the teachers' original predisposition and preferences.

As teachers connected with people in the online resource curation space, they connected with both school and district colleagues, extending collegial relationships online (Wellman, 2004), and established a large number of new ties with those who they only encountered online. Findings indicate that teachers were influenced mainly by their online-only peers, and they were not impacted by the resource curation activity of their school and district colleagues. It is possible that online-only peers tend to circulate resources that are novel to teachers, while school and district colleagues tend to distribute resources that teachers are already aware of. Indeed, previous studies have found that people rely on weak ties to acquire information and knowledge (Bakshy et al., 2012; Granovetter, 1973; Ruef, 2002), while they regard strong ties as social support, which tend to have repeated content and are not a good source to acquire diverse sets of information (Friedkin, 1982; Krackhardt, 2003; Liu et al., 2020).

Teachers in different career stages rely on and utilize their online networks in a different fashion. Findings indicate that teachers in the early stages of their career were influenced less by network members' curation activity compared to their experienced counterparts. This may be because experienced teachers developed a better system to identify professionals who could be a good source of professional support and can recognize who they can trust for quality resources among a pool of all other possible peers (Frank et al., 2020). In contrast, early career teachers may face uncertainties in composing and utilizing social capital in their online networks and converting them to be an effective professional support. In fact, this dissertation did not find a significant marginal effect of career stage on teachers' resource curation, indicating that there was little difference between teachers in different career stages with respect to how they curated resources; they differed only in how they allowed the online networks to influence the resources they curated. Indeed, if early career teachers are yet to know how to take advantage of the online networks, taking the time to explore resources curated by their network members means extra effort beyond seeking resources by themselves (Frank et al., 2011). As teachers stepped into the later stage of their career, they developed the ability to identify trustworthy network members that they can rely on when they need additional resources.

Moreover, I explored how teachers in different career stages respond to different sources of professional support, i.e., the resource curation activity from school and district colleagues and from online-only peers. Results indicate that teachers in different career stages were equally unresponsive to the network influence from school and district colleagues on Pinterest. Nevertheless, early career teachers were significantly less influenced by the resource curation activity of their online-only peers. This indicates that for early career teachers to curate certain resources, they were neither influenced by school and district colleagues nor by online-only peers; while experienced teachers were significantly influenced by their online-only peers. This finding is consistent with Liu et al. (2020), in which their previous study found no significant network effect of school and district colleagues when they modeled the first occurrence of teachers' pinning of a resource in a sample of early career teachers during the school year of 2015-16.

Building on the previous study, this dissertation further included both early career and experienced teachers and used data from the school year of 2016-17 with a full range of teachers' online networks encompassing both teachers' school and district colleagues as well as online-only peers. The nonsignificant finding of network influence from school and district colleagues could be due to either those colleagues only taking up a small proportion of teachers' online networks (6.21%, i.e., 5.65 out of 144.07 ties in teachers' online networks), or the information shared by those colleagues was not novel and hence did not cause teachers to curate that resource. In combination with the marginal effect of network influences from two different sources of social capital, teachers are responsive to the network influence from online-only peers—particularly the experienced teachers are more influenced by the resource curation activity of their online-only peers. Though teachers at the early career stage did not know how to leverage their online networks for resource curation, as they transitioned into the later stage of the teaching profession, they started to take advantage of their online networks, especially of those who are in the educational field but who they do not have direct contact with in their everyday school setting (Greenhow & Galvin, 2020; Henderson et al., 2013; Szeto et al., 2016).

Not all resources in teachers' social context led to teachers' activity of resource curation equally. This dissertation finds that facilitating materials (like data tracking binders, progress monitoring sheets, parent teacher conference rubrics, and fun project ideas) are the ones teachers are most likely to be influenced by in their online networks. This could be because facilitating materials are the type of resource that are suited for a broad range of teaching contexts, while Subject-Specific and Classroom Management resources may require teachers' further screening and examination in terms of how appropriate it is to their local teaching context. In a sense, once teachers are exposed to the facilitating classroom resources curated by their online networks, they rely on their network members for this type of resource and save them in their resource portfolio, knowing that they will sooner or later need them to support their teaching-related tasks. Careful discretion is required for interpreting the result that teachers were more likely to be influenced when they were exposed to Social and Emotional Learning resources in their social context, as the result was at the borderline significance level. The non-significant marginal effect of resource type indicates that teachers did not favor any specific type of resources in their curation process. Teachers need assorted kinds of resources when they prepare for lesson planning and seek additional materials online.

Discussion on Results with Caution

The grade level taught represents teachers' teaching context that is associated with students' developmental trajectory and the learning demands of students by a particular age group. Findings indicate that teachers who taught students in mid-elementary grades (i.e., grades two and three) were influenced more by the resource curation activities of their online networks. This might be due to the standardized assessment requirement in the State of Indiana, in which students from grade three begin to take the accountability assessment (Knake et al., 2021), and teachers in the mid-grades are under the pressure of testing and rely on their online networks as sources of professional support for additional resources for test preparation. This result should be interpreted with discretion as 2.72% of the estimates would have to be due to bias to invalidate the inference (Frank et al., 2013).

Periphery online secondary sites, such as Facebook and Instagram, which were not initially developed for distributing educational resources, tend to be social media platforms that feature a good display layout and communication channel. Thus, teachers might be attracted to resources from these origins once they observed them in their social context. Caution should also be taken when interpreting the moderating effect of resources that originated from the periphery online secondary sites on the network exposure effect. Though 22 out of 55 teachers curated resources from the periphery online secondary sites, only six out of 81 resources were coded in this category (i.e., 7.41%), meaning that there was not enough data on resources from this category to represent its specific network exposure effect.

Regarding the moderating roles of teachers' perceptions of teaching on the network exposure effect, results go in different directions. Specifically, teachers that excelled at classroom management, those who believed that state test expectations supported their ability to enact classroom instruction, and those that were facing a difficult learning environment all chose to be influenced and relied on their online networks for professional support. Online social networks are social capital and the information embedded provides professional learning opportunities for teachers who are in challenging teaching situations and are in need of additional support beyond what they have received at school (Frank & Torphy, 2019; Hu et al., 2018; Torphy et al., 2020). Nevertheless, the mixed finding did not support my hypotheses that teachers who were competent in classroom management and felt positive with test expectations may rely less on their online networks. Admittedly, these secondary analyses were exploratory, and the results could be spurious, thus may require careful review.

LIMITATIONS AND FUTURE DIRECTION

This dissertation attempted to account for potential confoundedness of the resource-mediated social selection process in teachers' resource curation when estimating the social influence process. I specifically estimated teachers' latent space positions in combination with that of resources in a social space defined by two-mode networks, as I believe that the two-mode social space was the social context that directly nurtured teachers' particular resource curation activities and gave birth to the subsequent social selections. Nevertheless, results indicated that the resource-mediated social selections in two-mode networks barely confound with the social influence process in teachers' resource curation activities in one-mode interpersonal networks. An alternative way to account for the social selection process using the latent space approach is to analyze the one-mode Waters District teachers' online networks (i.e., a network that only contains connections between teachers and no resources—social learning events—involved), treat the estimated latent positions as individual latent attributes at the teacher level, and control them in the relational-event social-influence model (Xu, 2016). Future research can explore how the latent social space defined by two-mode teacher-resource networks differs from that of one-mode teachers' online networks; and compare how the controls of the latent positions from two-mode networks are different from the controls of the latent positions from one-mode networks when estimating the social influence model.

Due to the population-related feature of the relational event model (REM) and of the latent space model (LSM)—which are used to model data at the group level—this dissertation only involved 81 prevalent resources that had at least four teachers curating them to avoid either low incidence of teachers' curation occurrence or floating ties of resources only curated by a few teachers. In other words, 589 less-prevalent resources were excluded, and no efforts have been put into modeling the social influence process around the less prevalent resources. Nonetheless, the social influence model, apart from the REM and LSM, can be estimated if egocentric network data is collected with longitudinal data on egos' and alters' resource curation activities. Future investigations can estimate the network exposure effect and its interaction effects with individual attributes, as well as the resource curation context around less-prevalent resources, and then compare the difference between the network exposure effect around prevalent and less-prevalent resources.

Quantitative analyses in this dissertation indicated a significant moderating effect of teachers being exposed to facilitating classroom resources in their social context and their subsequent resource curation activities. Yet, it is unclear why teachers are influenced more by their online networks regarding this type of resource. I plan to explore teachers' and their network members' resource curation data with respect to the attributes of these facilitating classroom resources, the time of the year that teachers curated these resources, and the distribution of the network exposures around these resources.

APPENDICES

APPENDIX A.

81 Resources Curated by at Least Four of the 55 Waters School District Teachers During the 2016-2017 School Year

Figure A1. Resource-Classroom management1
Description. Blurt beans are AWESOME for helping kids not interrupt and earn fun rewards Read this
Link.
http://missgiraffesclass.blogspot.com/2016/10/25-chatty-class-classroom-management.html

Figure A2. Resource-Growth mindset1
Description. Do you teach your students about growth mindset Are you aware of the benefits
Link.
http://www.kirstenskaboodle.com/affirmations-student-growth-mindset/

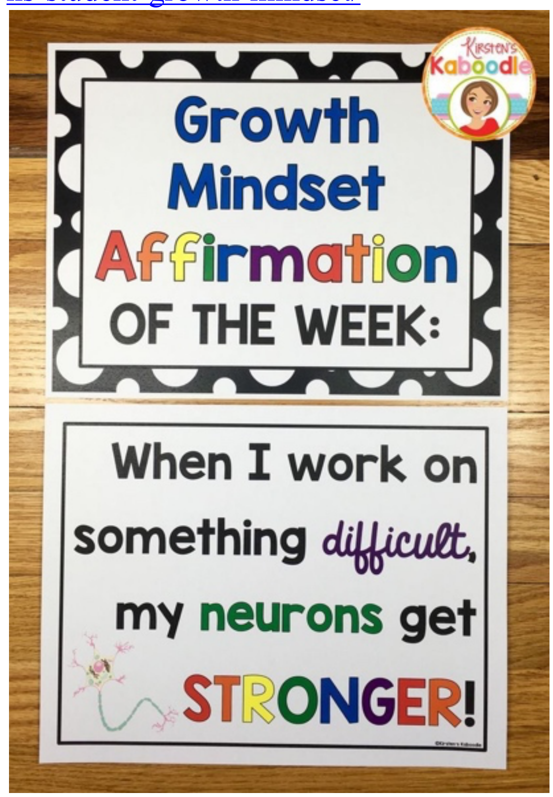


Figure A3. Resource-Classroom resource1
Description. 60 Must Make Kindergarten Anchor Charts for the classroom Covers classroom management, literacy and math Multiple ideas
Link.
http://kindergartenchaos.com/must-make-kindergarten-anchor-charts/

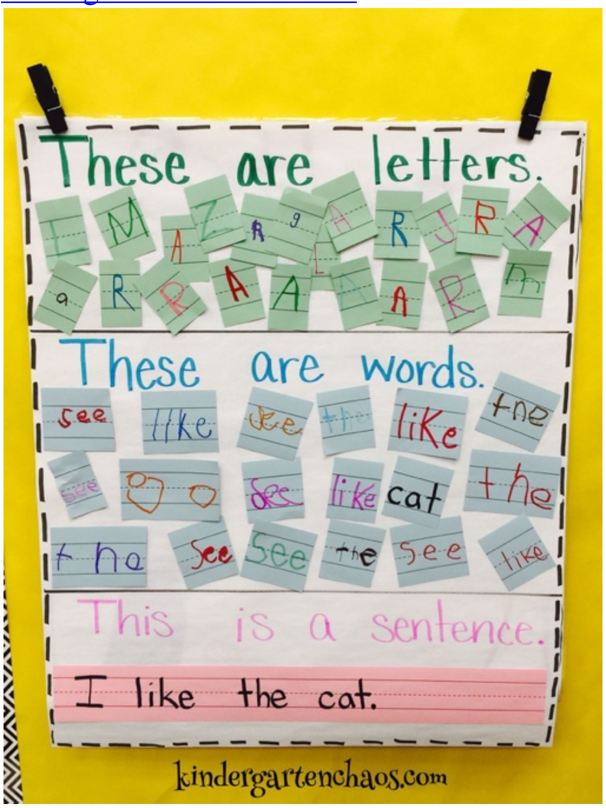


Figure A4. Resource-Growth mindset2
Description. Growth Mindset Read Alouds

Link.
http://primarychalkboard.blogspot.com/2015/07/growth-mindset.html?m=1

Figure A5. Resource-Flexible seating1

Description. Budget friendly flexible seating options

Link.
http://teach2love.blogspot.com/2016/04/flexible-seating.html

Figure A6. Resource-Classroom management2

Description. Goal cards taped to kids desks When they reach them they are moved to kids binders I think I would put them on a bulletin board classroom management

Link.
https://www.facebook.com/groups/849939608418144/permalink/1202101619868606/

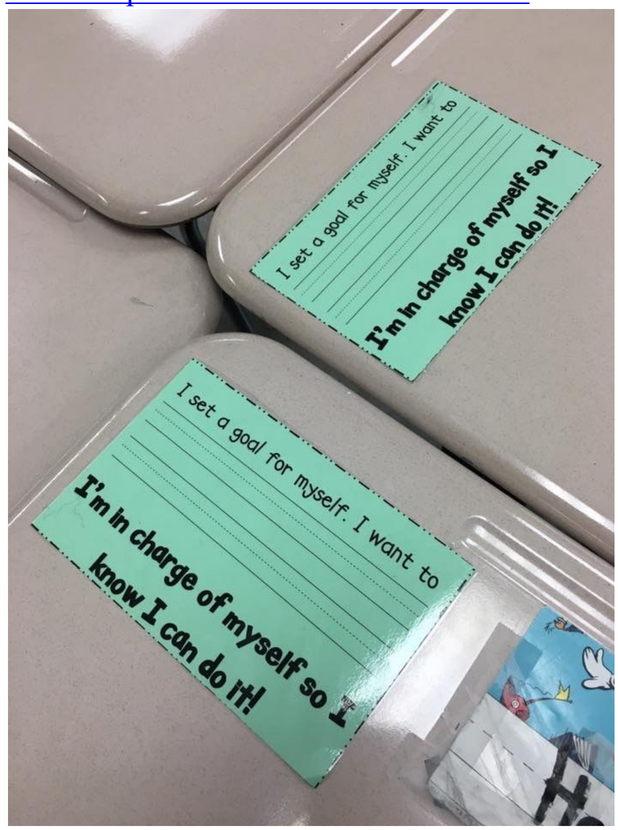


Figure A7. Resource-Growth mindset3
Description. Encourage students to realize the power of growth mindset and the word aposyetapos with this read aloud and free graphic organizer
Link.
http://brownbagteacher.com/growth-mindset/

Figure A8. Resource-Character education1
Description. Responsive Classroom Activities Pin it Like Image

Link.
http://www.pinterest.com/pin/155866837076835683/

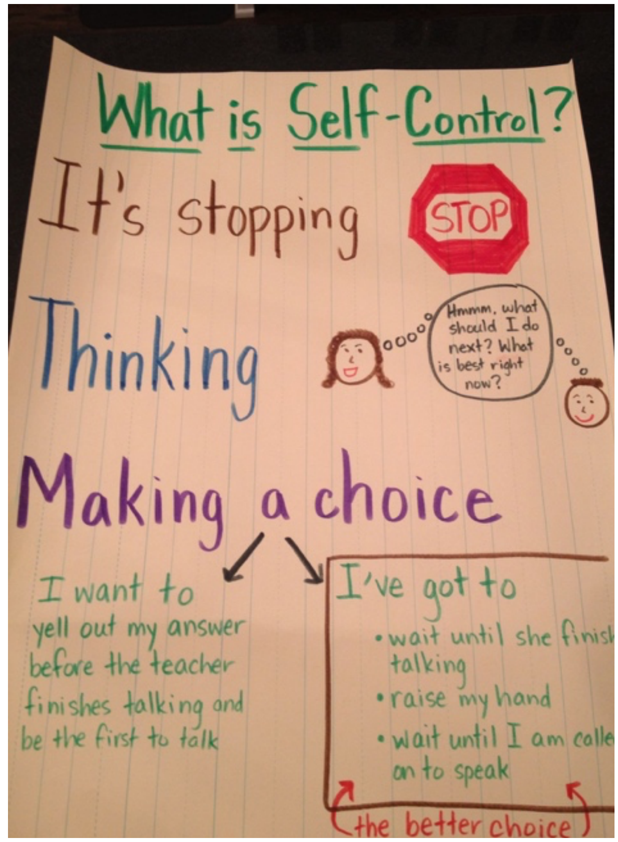


Figure A9. Resource-Classroom management3
Description. Staple a Speeding Ticket to a sloppy paper, send home, and have the student redo the assignment
Link.
http://www.teach123school.com/2016/05/busy-teacher-forms.html

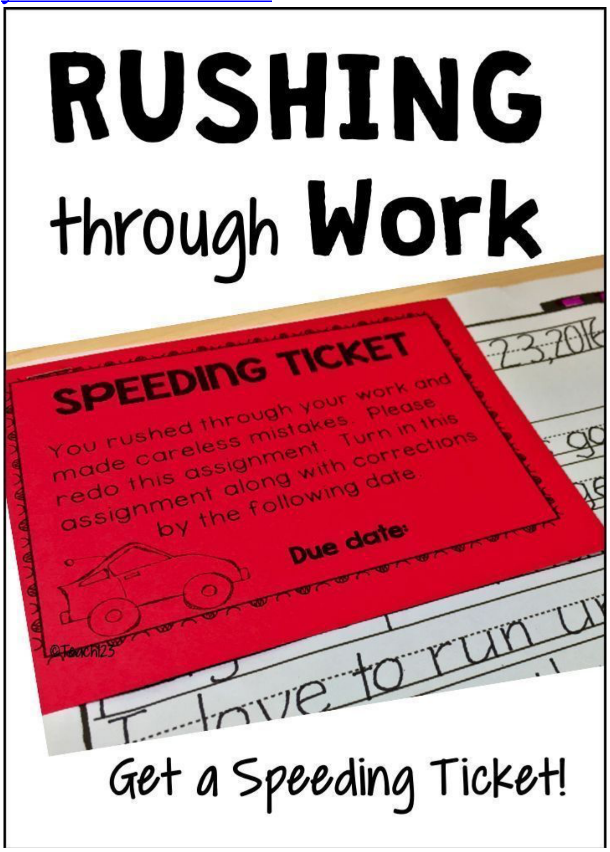


Figure A10. Resource-Flexible seating2
Description. Flexible seating
Link.
https://www.instagram.com/p/BEWnPUizQyT/

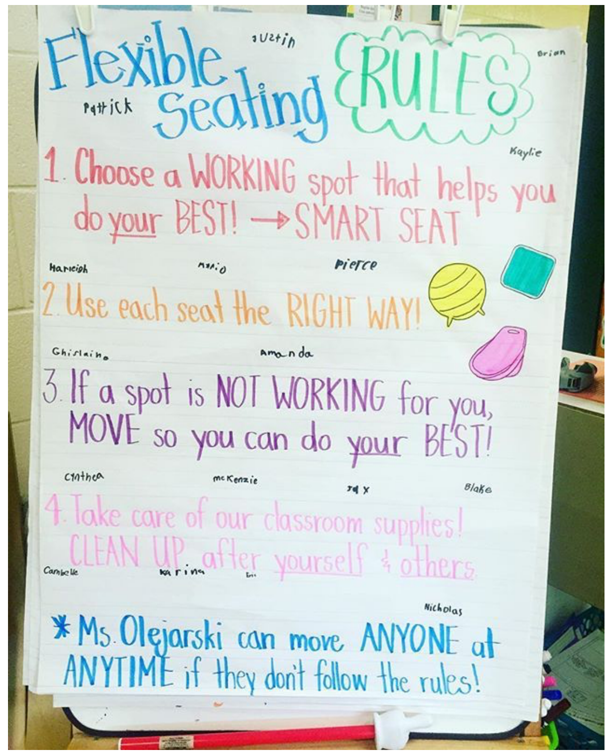


Figure A11. Resource-Writing1
Description. Sentence swag anchor chart

Link.
https://www.teacherspayteachers.com/Product/Parent-Notes-1943146

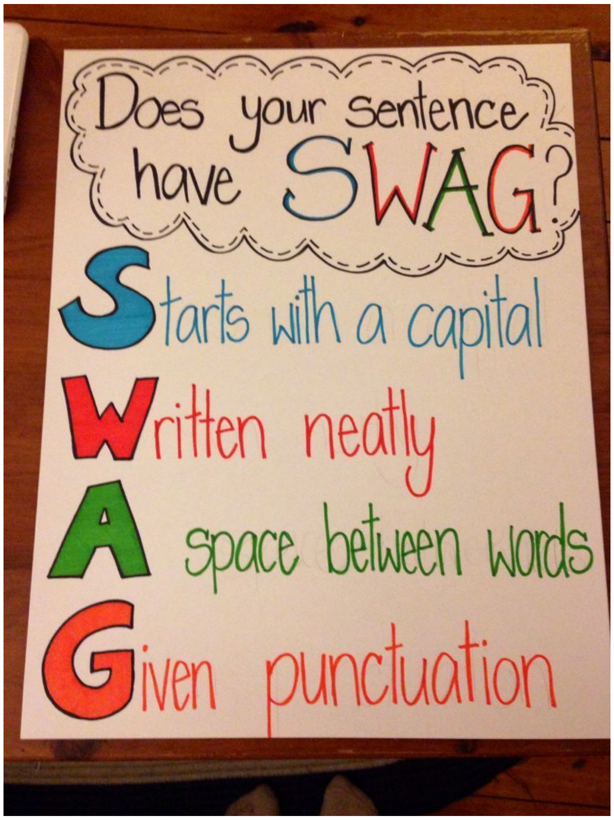


Figure A12. Resource-Reading2
Description. Learning to read resources and ideas that will help build reading fluency
Link.
http://missgiraffesclass.blogspot.com/2015/09/short-activities-and-resources.html

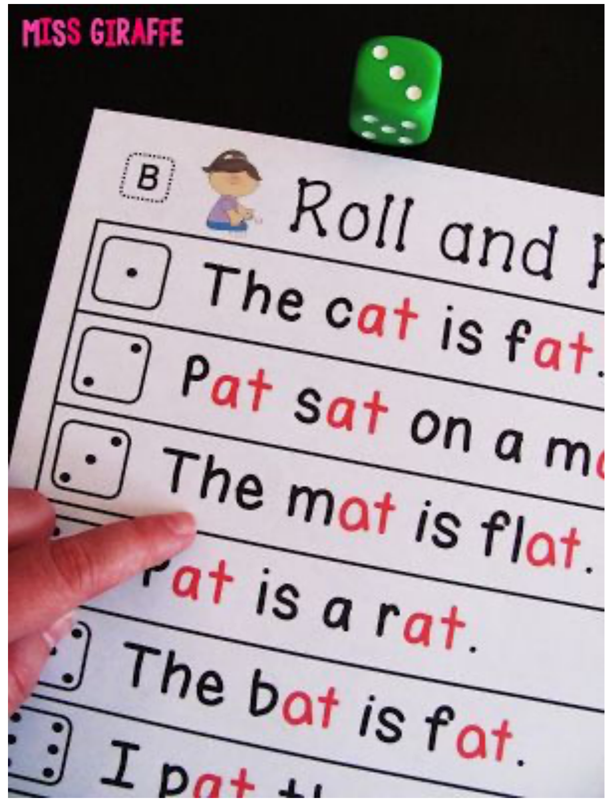


Figure A13. Resource-Classroom management6

Description. 25 Chatty Class Classroom Management Tips that are quick and easy to get an overly talkative class under control

Link.

http://missgiraffesclass.blogspot.com/2016/10/25-chatty-class-classroom-management.html?m=1

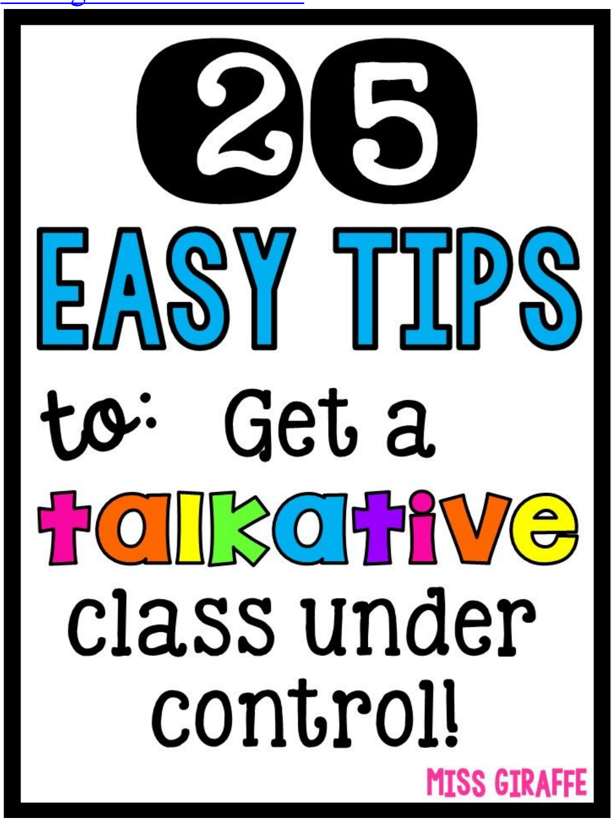


Figure A14. Resource-Writing3

Description. Mrs Terhunes First Grade Site Search results for Opinion writing

Link.

http://mrsterhune.blogspot.com/2012/01/anchor-charts.html

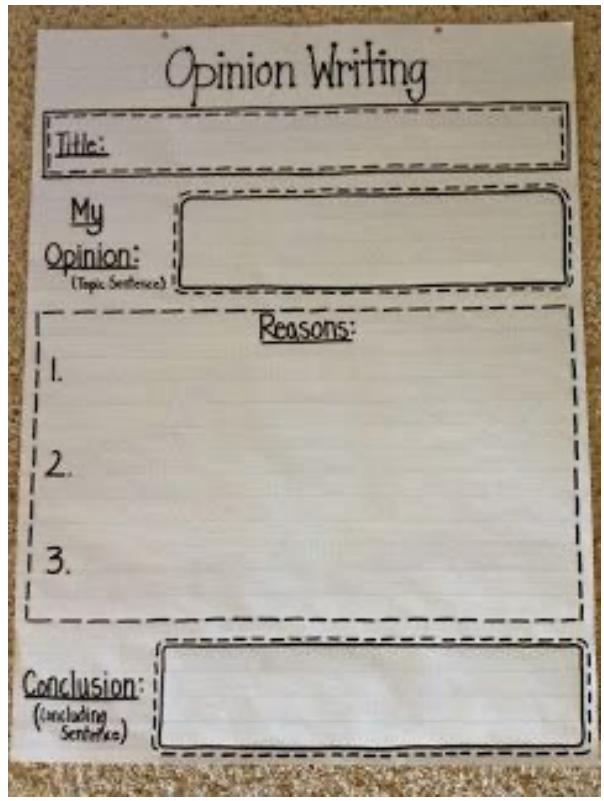


Figure A15. Resource-Growth mindset4
Description. Principal Growth Mindset Is Making a Difference at Munford Elementary Blog
Link. http://www.bestpracticescenter.org/blog/principal-growth-mindset-is-making-a-difference-at-munford-elementary

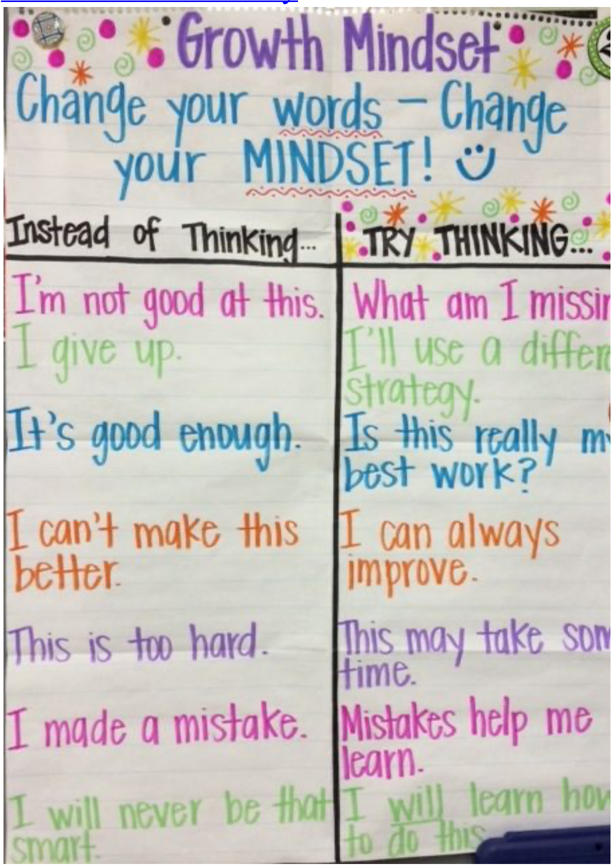


Figure A16. Resource-Writing2
Description. Personal Narrative Anchor Chart

Link. http://www.mrsrichardsonsclass.com/9-must-make-anchor-charts-for-writing/

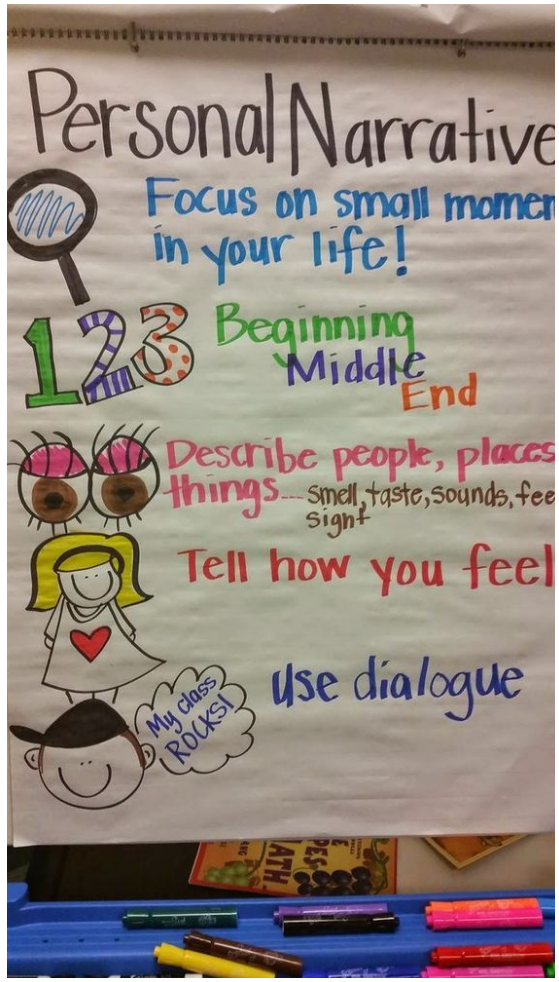


Figure A17. Resource-Classroom management5
Description. Change your classroom today by banning the words Im done Improve work quality and deter those fast finishers
Link.
http://www.teachertrap.com/2016/01/outlaw-im-done.html/

Figure A18. Resource-Classroom management4
Description. Classroom Management Makeover

Link.
http://www.teachertrap.com/2016/06/classroommanagement.html/

Logical Consequences Cheat Sheet

OUTSIDE THE CLASSROOM

Student Behavior	Logical Consequence
Walking in Line: Too loud or silly.	Walk with teacher and/or spend 2-5 minutes during recess practicing walking calmly and quietly.
Lunchroom: Too loud or crazy.	Sit at "silent table" the next day at lunch.
Recess: Too rough or unsafe.	Sit down and come up with 3 ideas for ways to play more safely. Apologize to other students.
Library: Too loud, running around.	Choose books from an assigned area that day.
Computer Lab: Playing around or getting off-task.	Complete pencil/paper work instead.
Restroom: Playing around.	Write a "rule book" for restroom breaks (during lunch or at home) and share with the class.
Restroom: Made a mess.	Clean the mess and write an apology to the custodian.
Anywhere: Disrespectful language to an adult.	Write a letter of apology (during lunch or at home).

INSIDE THE CLASSROOM

Student Behavior	Logical Consequence
Rushed through work.	Redo the work, this time doing best and taking time. (Right then, at lunch, or at home.)
Playing/off-task while working at group table.	Move to a more private, secluded spot to complete the work and/or apologize to classmates.
Playing or talking during independent work.	Lose privilege of choosing own spot that day and must work at desk during that time.
Broke a classroom supply or tool on purpose.	Write an apology to owner; come up with 3 ways to make amends. Lose privilege of using that supply.
Disruptive during whole class lesson.	Move to desk or private spot and/or create a written plan for how to be a helpful classmate and good student in the future.
Work refusal.	Complete the work as homework.
Rude or mean to classmate.	Write letter of apology and come up with 3 ways to make amends.

Explain the logical consequence in a calm and empathetic tone!
Allow the child to feel the effects of his/her actions!
Logical consequences are meant to TEACH, not punish.

Figure A19. Resource-Classroom resource2
Description. Students track their reading level Would be great to keep in a take home binder so parents can talk with them about it A great way to begin using data notebooks

Link.
https://www.teacherspayteachers.com/Product/Editable-Data-Binder-2007281

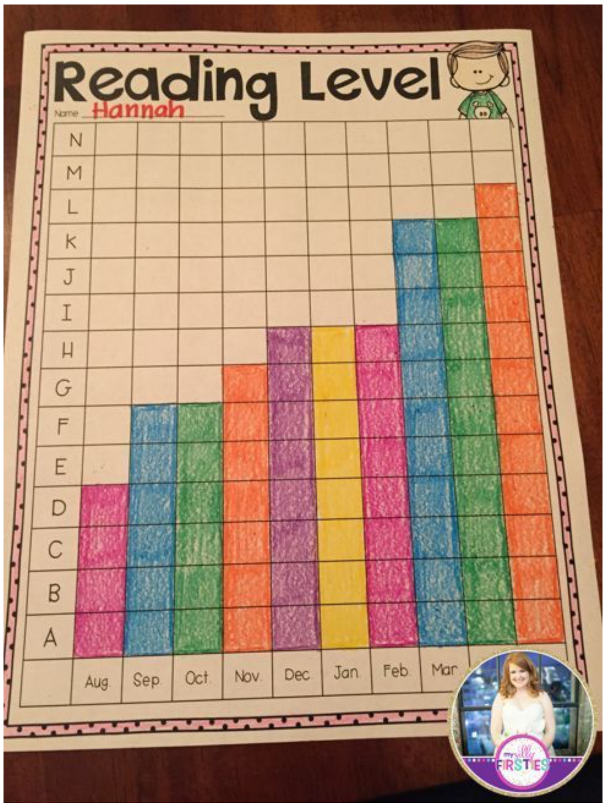


Figure A20. Resource-Growth mindset5
Description. Do your students have a growth mindset or a fixed mindset Here are some engaging activities for elementary kids These lessons are designed as a way to foster a Growth Mindset culture in your classroom with your students Also Included are bulletin board resources to display student work
Link.
https://www.teacherspayteachers.com/Product/Growth-Mindset-2614570

Figure A21. Resource-Reading3
Description. Guided Reading Note Cards for Teachers FREEBIE
Link.
https://www.teacherspayteachers.com/Product/Guided-Reading-Note-Cards-for-Teachers-FREEBIE-1508357

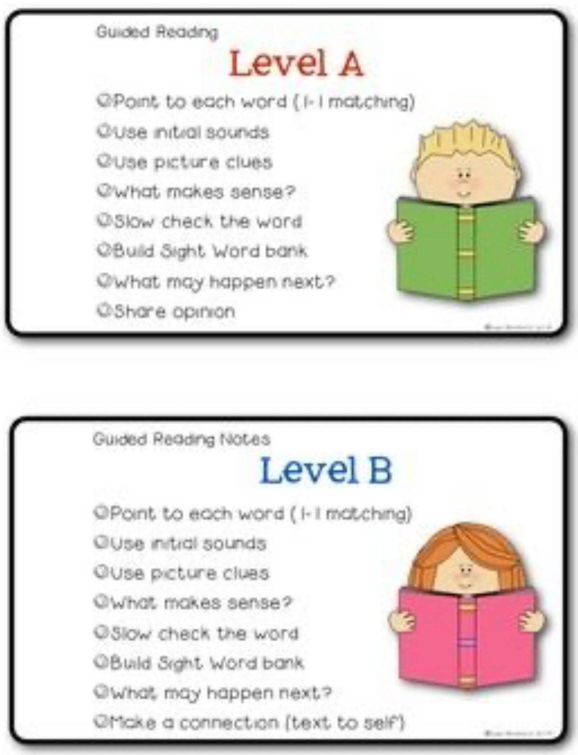


Figure A22. Resource-Reading1
Description. FREE Reading Strategies Bookmarks
Link.
https://www.teacherspayteachers.com/Product/Reading-Strategies-Bookmarks-2353244?aref=g4z1snml

Figure A23. Resource-Reading5
Description. Teaching Compare and Contrast with Songs

Link.
http://bookunitsteacher.com/wp/?p=4109

Figure A24. Resource-Math2
Description. Want a FREE differentiated place value game to use in your math centers tomorrow Read about how weve transformed the popular game Yahtzee into a fun and engaging place value game Youll even get our free score cards to use
Link.
http://games4gains.com/blogs/teaching-ideas/44100548-score-some-points-with-place-value-yahtzee

Figure A25. Resource-Reading4
Description. guided reading level a

Link.
http://mrsjonessclass.blogspot.com/2015/10/guided-reading-made-easy-level-a.html

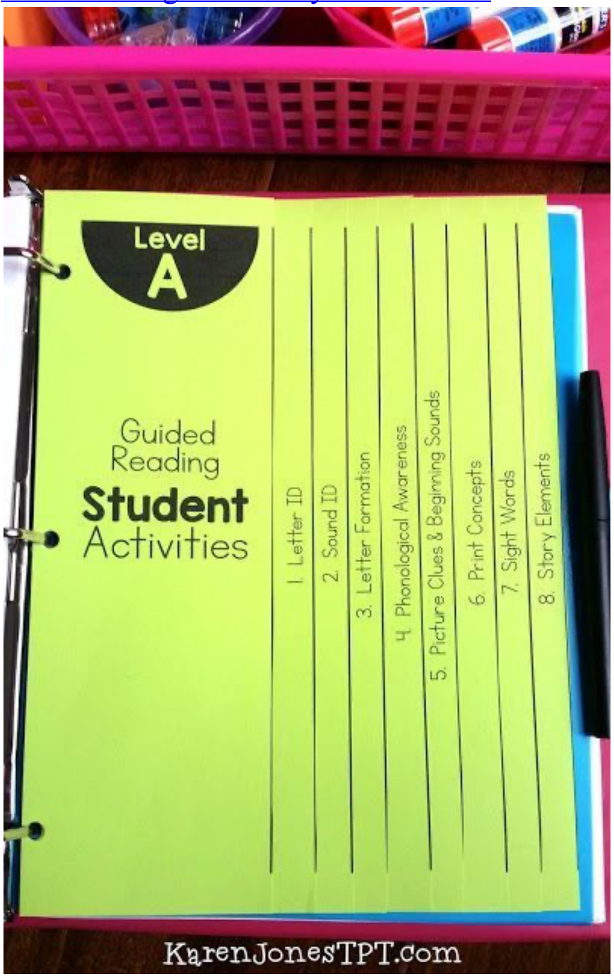


Figure A26. Resource-Math1
Description. Get Your GROOVE on with GUIDED MATH 10week blog series LEARN everything about
Link.
http://simplyskilledinsecond.com/2016/05/03/get-your-groove-on-with-guided-math/

Figure A27. Resource-Character education2
Description. New Year Goals 2017 More

Link.
http://theteacherbag.com/2015/12/27/new-years-resources-freebie/

Figure A28. Resource-Writing4
Description. 26 creative book report ideas so many really unique and FUN book report projects for kids of all ages Kindergarten 1st grade 2nd grade 3rd grade 4th grade and 5th grade homeschool writing
Link.
http://www.123homeschool4me.com/2015/08/26-book-report-ideas.html?m=1

Figure A29. Resource-Fun project1
Description. Reindeer Directed Drawing for Classrooms such a fun activity Great for ALL Ages
Link.
http://www.busykidshappymom.org/draw-reindeer-printable-directions/

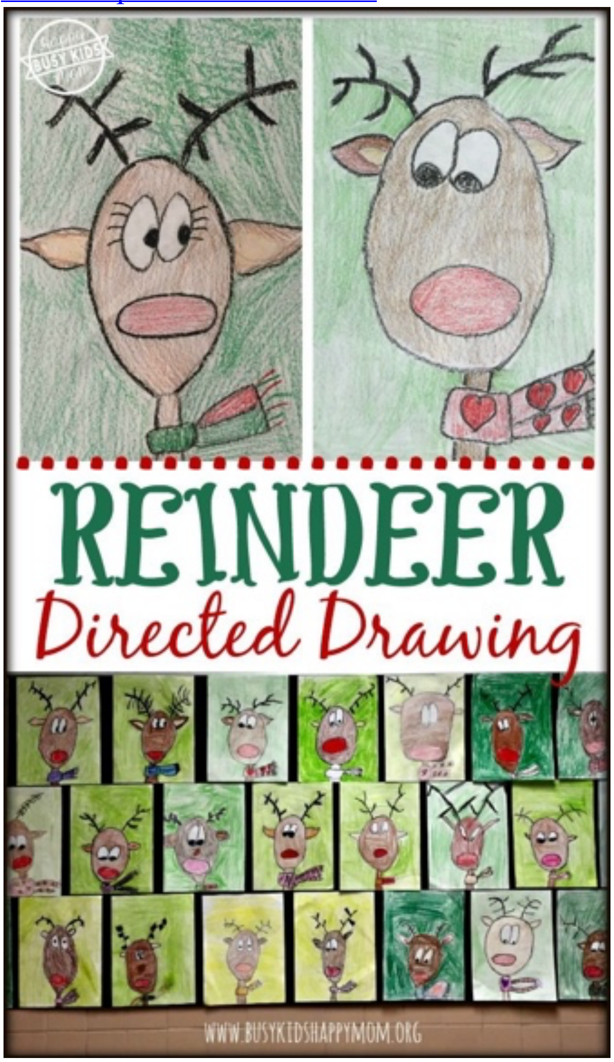


Figure A30. Resource-Character education3
Description. Free printable empathy game to help kids develop empathy for others

Link.
http://www.momentsaday.com/empathy-game/

Figure A31. Resource-Growth mindset8
Description. Mindset chart for students to complete
Link.
http://www.nerdynerdynerdy.com/2014/07/when-students-say-i-cant-do-it.html

Name: ____________________

GROWTH MINDSET
What Can I Say to Myself?

Instead of...	Try thinking...
I'm not good at this.	What am I missing?
I'm awesome at this.	I'm on the right track.
I give up.	I'll use some of the strategies we've learned.
This is too hard.	
I can't make this any better.	
I just can't do math. (or reading, or social studies, or writing, or science...)	
I made a mistake.	
She's so smart. I'll never be that smart.	
It's good enough.	
Plan A didn't work.	

Figure A32. Resource-Flexible seating3
Description. Flexible Seating Classroom
Sassy Savvy Simple Teaching
Link.
http://www.sassysavvysimpleteaching.com/2016/12/flexible-seating-classroom/

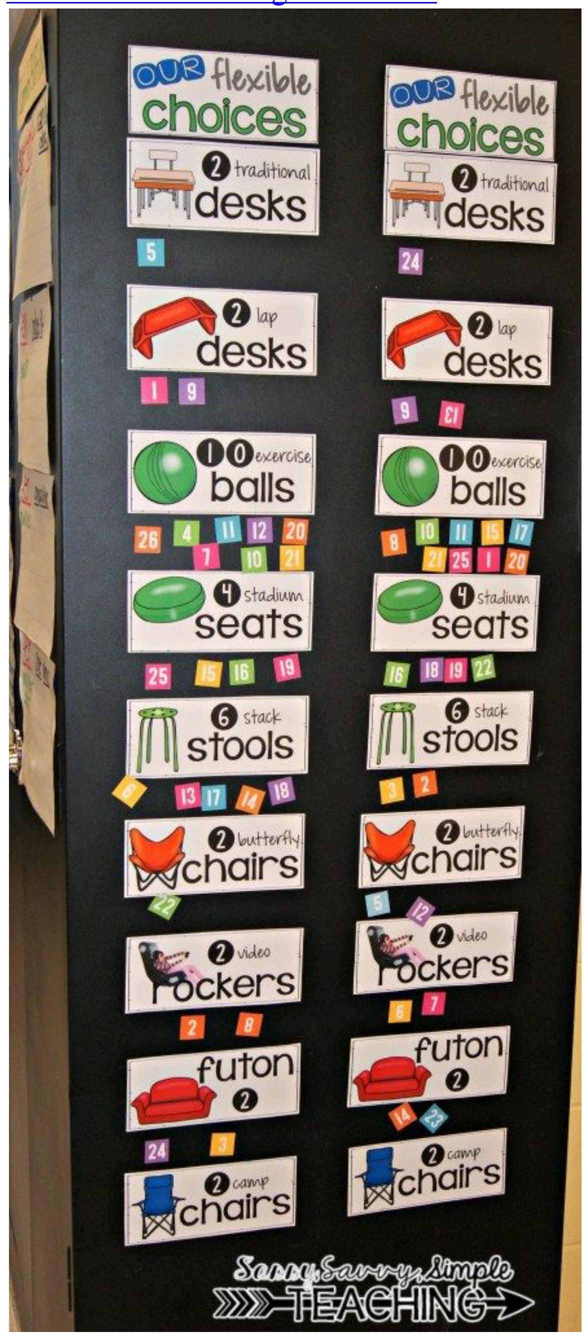


Figure A33. Resource-Classroom management7
Description. Anchor Charts for Classroom Management Scholasticcom

Link.
http://www.scholastic.com/teachers/top-teaching/2015/09/anchor-charts-classroom-management

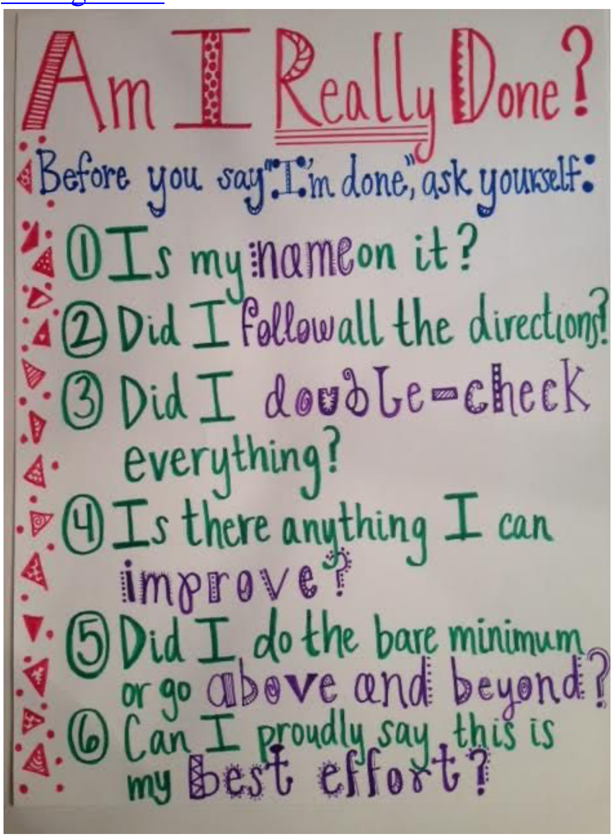


Figure A34. Resource-Growth mindset6

Description. A short movie for kids teaching growth mindset with a corresponding lesson plan More
Link.
http://www.teachingideas.co.uk/video/Soar

Figure A35. Resource-Classroom resource3
Description. FREEBIE ALERT 60 editable student data tracking binder pages from The Curriculum Corner

Link.
http://www.thecurriculumcorner.com/thecurriculumcorner123/2016/06/09/student-data-tracking/

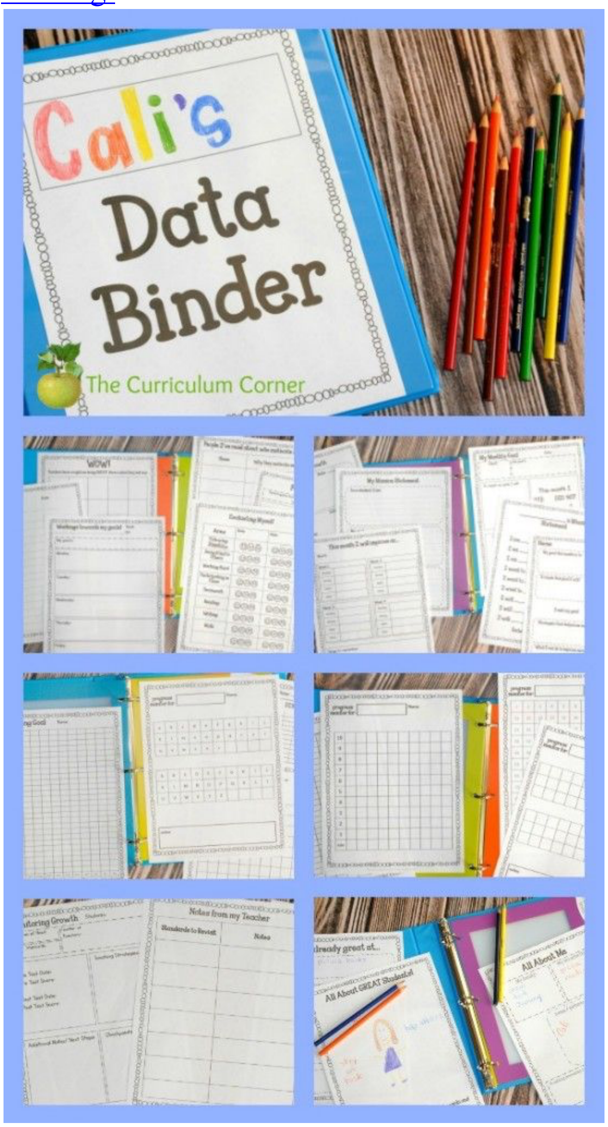


Figure A36. Resource-For parents1
Description. Parent Teacher Conference Form Checklist for students' strengths, areas for improvement. Open space to write in test results, grades, ways for parents to help at home. This form would make Parent
Link.
http://www.thehappyteacher.co/2015/09/parent-teacher-conferences-8-more-tips.html

Parent Teacher Conference Form

Student	Date/Time
Strengths	**Concerns**
❑ Asks for help ❑ Comes prepared ❑ Comes to class on time ❑ Completes homework ❑ Demonstrates self-control ❑ Does well on tests ❑ Follows directions ❑ Gets along with others ❑ Gives best effort ❑ Has a positive attitude ❑ Is respectful ❑ Listens well ❑ Participates in class ❑ Solves problems independently before asking for help ❑ Thinks creatively ❑ Accepts responsibility ❑ Good behavior in the cafeteria, gym, library, playground, specials	Student needs to ❑ Attend school every day ❑ Be on time to class ❑ Bring all materials ❑ Demonstrate self-control ❑ Remain seated during class ❑ Complete class work ❑ Participate appropriately ❑ Communicate respectfully with adults and peers ❑ Have a positive attitude ❑ Pay attention, focus, & listen ❑ Complete homework ❑ Keep hands, feet, and objects to himself/herself ❑ Speak at appropriate times ❑ Work collaboratively ❑ Unacceptable behavior in the cafeteria, gym, library, playground
Test Results & Grades	**Ways to Help at Home**
Comments/Notes	
Signatures	

The HAPPY Teacher

Figure A37. Resource-Back-to-school1
Description. 7 fun and fresh gettoknowyou activities for the beginning of the year including a Who Am I poster with flipflap clues A Maze of New Friends activity and more Perfect for backtoschool Gr 35 Click the image for details or see the bundle of BOTH my GettoKnowYou activity packs here httpswwwteacherspayteacherscomProductBUNDLEBacktoSchoolGetToKnowYouActivitiesFunFresh2Packs1984515
Link. https://www.teacherspayteachers.com/Product/Back-to-School-Get-To-Know-You-Activities-Fun-Fresh-1348248?pp=1

Figure A38. Resource-Growth mindset7
Description. Growth Mindset FREEBIE
Link. https://www.teacherspayteachers.com/Product/Growth-Mindset-FREEBIE-1988801

Figure A39. Resource-Reading11
Description. Must Do May Do System INSTEAD of rotating reading centers So much better Great blog with great ideas for guided reading time

Link.
http://1stgradepandamania.blogspot.com/search/label/MUST%20Do%20MAY%20Do

Figure A40. Resource-Fun project2
Description. 10 Principles Of Genius HourGenius Hour is a movement picking up traction globally an opportunity where students given true autonomy explore their own passions and exercise creativity in the classroom It allows pure voice and choice in what students learn during a set period of time during school Genius Hour is studentdriven passionbased inquiry at its best which can be enhanced by technology in the hands of modern learners Put simply it is a time where learners choose what to learn and how to learn ded318
Link.
http://anthsperanza.global2.vic.edu.au/2015/04/12/hacking-student-passions-through-genius-hour/

Figure A41. Resource-Spelling2
Description. Word work ideas each pencil case has a different way to practice spelling words. Spelling words houses in one locations. Students choose word list, grab a pencil case, and practice words. Only have to change the word lists
Link.
http://carrfw.blogspot.com/2012/08/third-grade-rocks.html?m=1

Figure A42. Resource-STEM challenge2
Description. Candy Cane Experiment free from First Grade Wow

Link.
http://firstgradewow.blogspot.com/2015/12/grinning-with-that-green-guy.html?utm_source=feedburner&utm_medium=email&utm_campaign=Feed:+FirstGradeWow+(First+Grade+Wow)

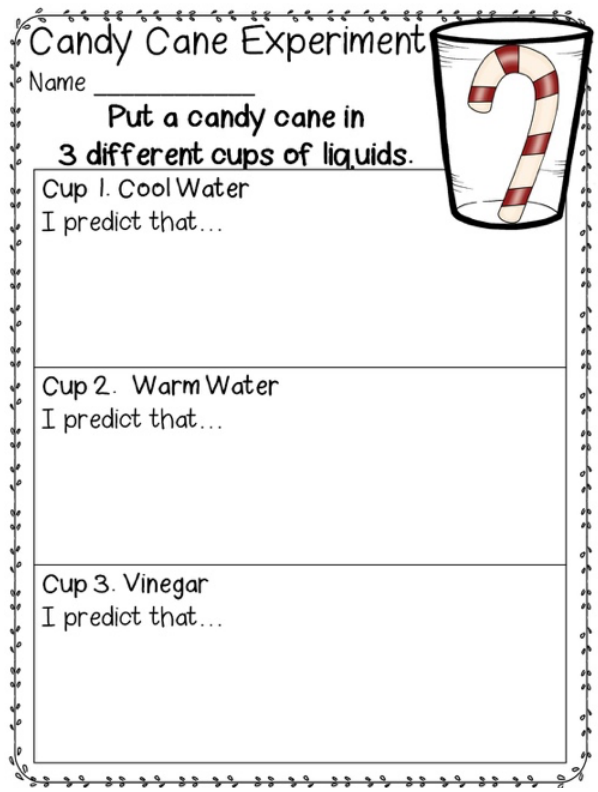


Figure A43. Resource-STEM challenge1
Description. Remove the first cup they start falling in a domino effect 4 Engineering Challenges for Kids with Cups Craft Sticks and Cubes Fun for rainy days scheduled via httpwwwtailwindappcomutm_sourcepinterest utm_mediumtwpinutm_contentpost9570100utm_campaignscheduler_attribution
Link.
http://frugalfun4boys.com/2015/06/11/4-engineering-challenges-kids/

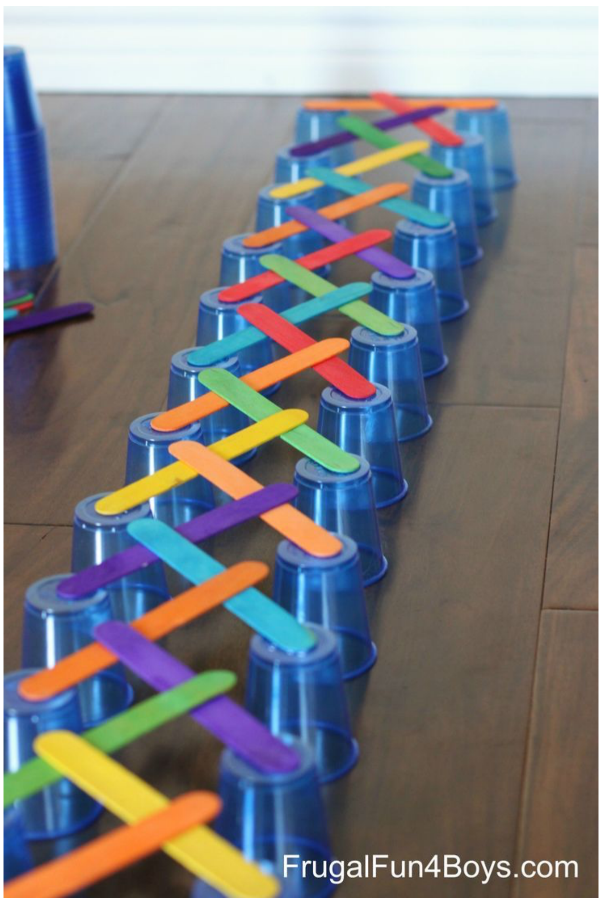


Figure A44. Resource-STEM challenge3
Description. 5 Engineering Challenges with Clothespins, Binder Clips, and Craft Sticks. Awesome STEM activity for kids

Link.
http://frugalfun4boys.com/2016/05/08/engineering-challenges-clothespins-binder-clips-craft-sticks/

Figure A45. Resource-Classroom resource4
Description. Superhero Classroom Bulletin Board 25 Creative Bulletin Board Ideas for Kids httphativecomcreativebulletinboardideasforkids
Link.
http://hative.com/creative-bulletin-board-ideas-for-kids/

Figure A46. Resource-STEM challenge4
Description. Christmas Tree Stem Play Dough and Straws Christmas tree building

Link.
http://littlebinsforlittlehands.com/christmas-stem-ideas-kids/

Figure A47. Resource-Spelling4
Description. What a great anchor chart for how to spell on your own picture only

Link.
http://media-cache-ak0.pinimg.com/736x/16/0d/92/160d92339059ba77b7b869290e1435dd.jpg

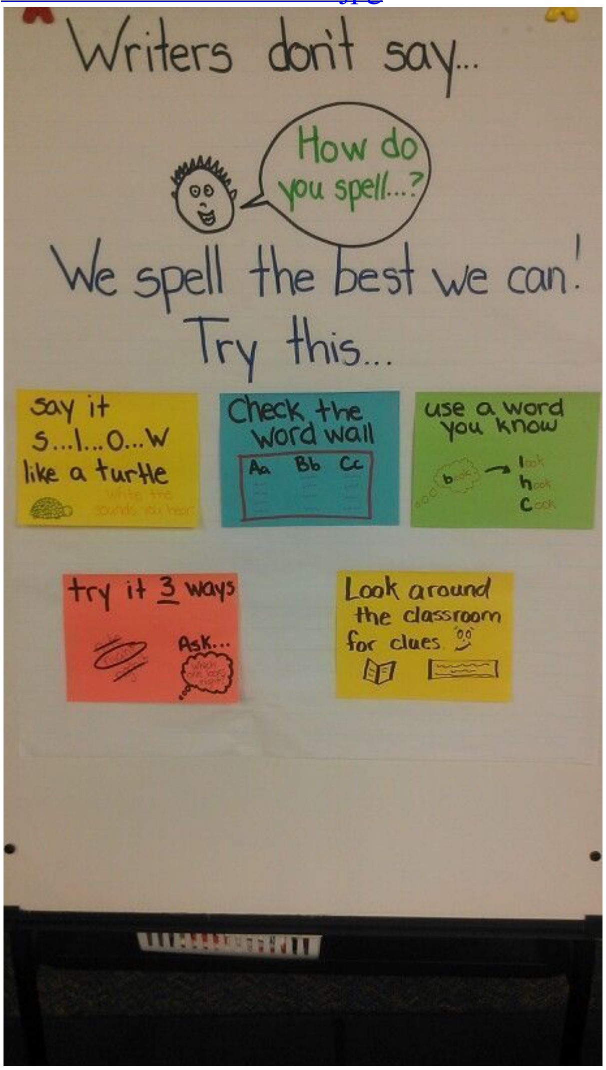


Figure A48. Resource-Math3
Description. Fact Fluency in First Grade COVER ME UP Dominoes center where each kid gets a game board and covers the sum their domino makes click for a ton of activity ideas
Link.
http://missgiraffesclass.blogspot.com/2016/01/fact-fluency-in-first-grade.html

Figure A49. Resource-Math4
Description. Bookmark this page for a lot of awesome first grade math ideas this one is all about addition to 20 but there are ideas for almost every concept
Link.
http://missgiraffesclass.blogspot.com/2016/01/making-10-to-add.html

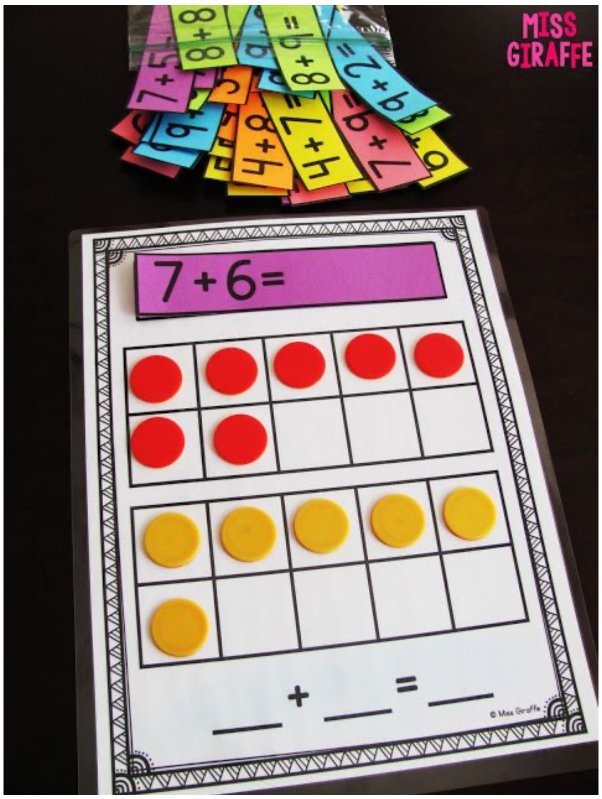


Figure A50. Resource-Writing5
Description. We have a saying in our class to Dig Deep with our writing Digging Deep is where we practice writing more detailed sentences to mak
Link.
http://mrshinersheadlines.blogspot.com/2013/10/digging-deeper-with-our-writing.html?m=1

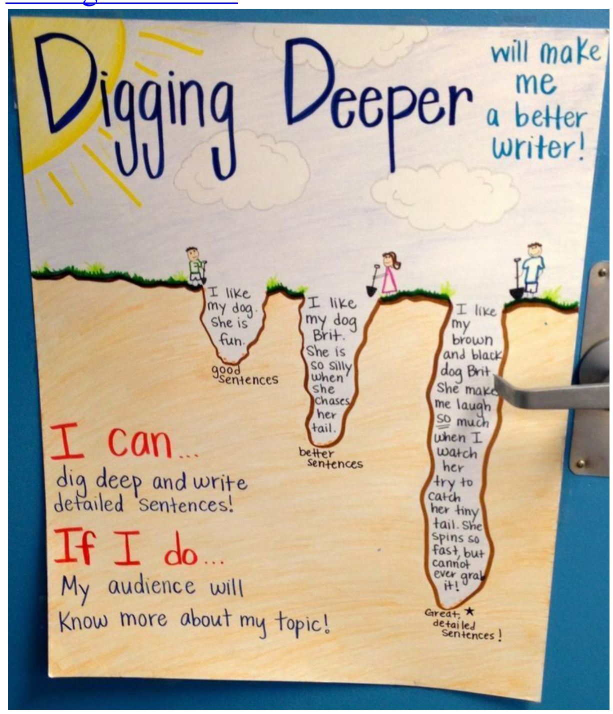


Figure A51. Resource-Character education4
Description. Mrs Terhunes First Grade Site Anchor Charts

Link.
http://mrsterhune.blogspot.com.au/search/label/Anchor%20Charts

Figure A52. Resource-For parents2
Description. Once Upon a First Grade Adventure How to Approach Parent Teacher Conferences Like a Pro
Link.
http://onceuponafirstgradeadventure.blogspot.com/2015/10/how-to-approach-parent-teacher.html

Figure A53. Resource-Classroom management9

Description. Are you an elementary classroom teacher that is tired of your kids moving and getting supplies when you are giving directions Check out this simple easy to implement classroom management strategy

Link. http://peppyzestyteacherista.com/2016/05/classroom-management.html?platform=hootsuite

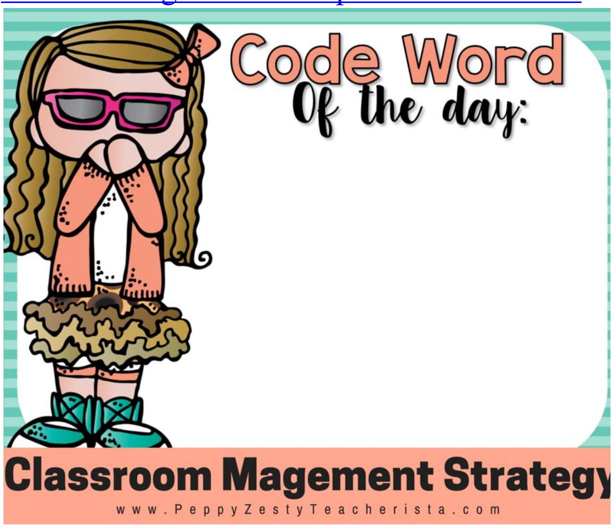


Figure A54. Resource-STEM challenge7

Description. Blog post outlines 5 fun fabulous Halloweenthemed STEM challenges that can be modified for use with grades 28

Link. http://plansforabettertomorrow.blogspot.com/2015/10/halloween-stem-olympics_10.html

Figure A55. Resource-Back-to-school2
Description. Beginning of the Year Read Alouds So excited
Link.
http://secondgradealicious.blogspot.ca/2014/07/beginning-of-year-read-alouds-so-excited.html

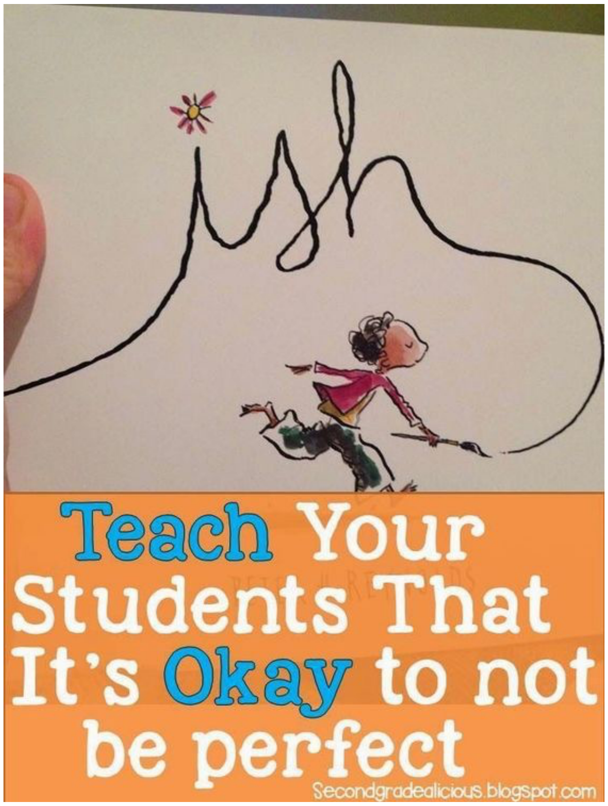


Figure A56. Resource-Character education5
Description. Full of great ideas to help you teach character traits in reading
Link.
http://the-teacher-next-door.com/index.php/blog/57-blog-reading/16-teaching-character-traits-in-reading

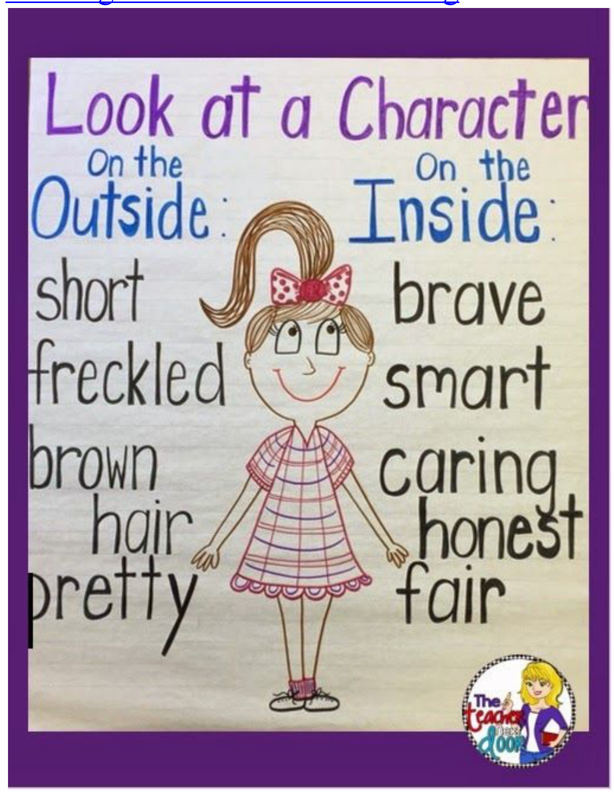


Figure A57. Resource-Classroom management8

Description. Social Problem Solving Posters FREE

Link. http://thisreadingmama.com/social-problem-solving-posters/

Figure A58. Resource-STEM challenge5

Description. New science activity for kids using STEM Science Technology Engineering and Math education science activity for elementary students that requires students to explore how different liquids affect MMs

Link. http://www.firstgradenest.com/2014/03/stem-m-soaking.html

Figure A59. Resource-Reading6
Description. Reading Response Questions for Any Book Freebie

Link.
http://www.fourthnten.com/2014/01/my-fourth-grade-homework-routine.html

Fiction Responses

1. What character do like the most in your book? Why?
2. What do you predict will happen next in this story? What information in the text helped you make that prediction?
3. What is the main problem of the story? If you know, how was the problem solved?
4. Would you like to be a character in this story? Why or why not?
5. How do you feel about this story? Would you recommend it to someone else? Why or why not?
6. Summarize what you read today. What were the most important events? Did you learn anything new about the characters?
7. Is what you read believable? Why or why not?
8. Pretend you are interviewing the main character of the story. What two questions would you ask them?
9. If you could trade places with one of the characters, who would it be? Why?
10. Is there anything you would change about this story? What would it be? Why would you change it?

Non Fiction Responses

1. What is the selection you read mainly about?
2. What did you learn while reading?
3. Why did the author probably write this selection? How do you know?
4. What was the main idea of what you read? What were the supporting details that told you more about the main idea?
5. How and where could you find out more information about the topic read about today?
6. What else would you like to know about the topic you read about?
7. Were there any text textures that helped you better understand your reading? What were they and how did they help you?
8. What did you find interesting about this selection?
9. What do you remember most about the selection you read?
10. Did you find an interesting word in this selection? What was it? Use a dictionary to find out its meaning and write a sentence of your own using that word.

Fourth and Ten

Fourth and Ten, 2012, 2014

Figure A60. Resource-Reading7
Description. Description. Guided reading charts for kindergarten-this is something I wish I would've
Link.
http://www.kindergartenworks.com/guided-reading/guided-reading-mats/

Figure A61. Resource-Growth mindset11
Description. Are you teaching your students about growth mindset Do they understand how the brain works Use Your Fantastic Elastic Brain to deepen your students understanding of growth mindset This blog post

Link.
http://www.kirstenskaboodle.com/growth-mindset-activities-fantastic-elastic-brain/

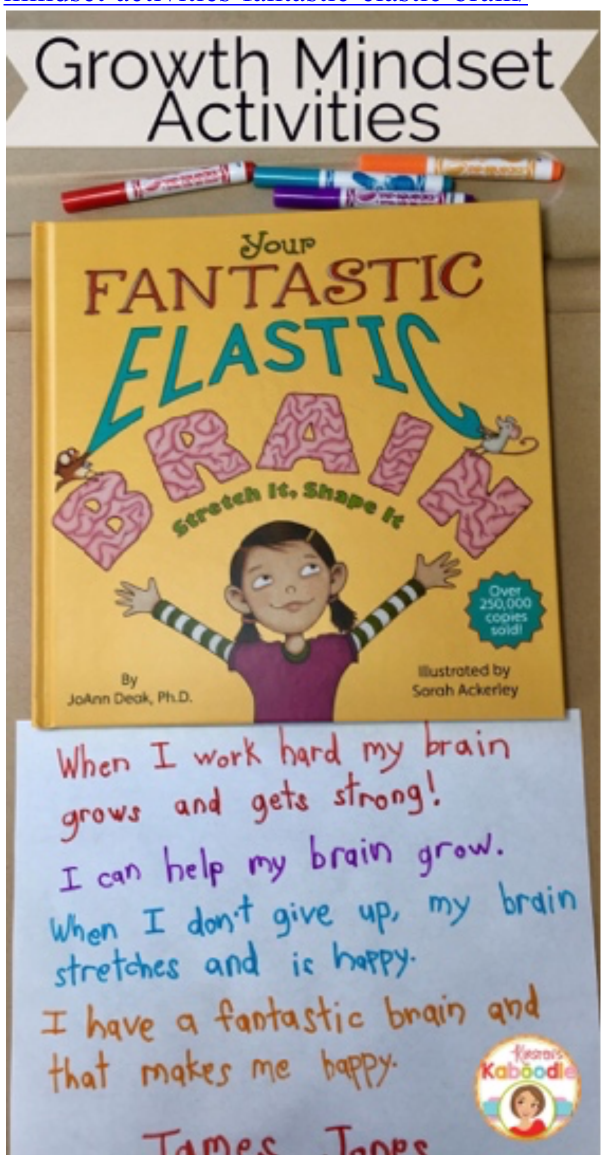


Figure A62. Resource-Growth mindset10
Description. Are you teaching your students about growth mindset These books by Kobi Yamada are perfect for helping students understand how to reframe issues What Do You Do With and Idea and What Do You Do With a Problem are an easytouse brilliant resource for your classroom
Link.
http://www.kirstenskaboodle.com/picture-books-growth-mindset-kobi/

Figure A63. Resource-Growth mindset9
Description. Two FREE growth mindset posters to get your students thinking Emoji Style From Light Bulbs and Laughter

Link.
http://www.lightbulbsandlaughter.com/2016/07/self-assessment-tools-emoji-style.html

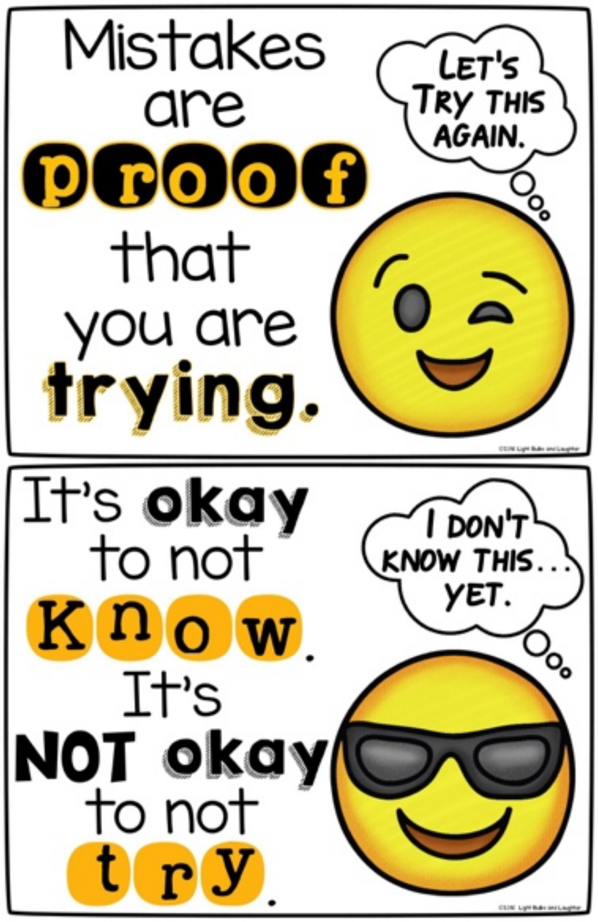


Figure A64. Resource-Flexible seating4
Description. Are you thinking about flexible seating for your classroom Alternative seating can improve student focus increase student participation and motivate your learners Here are some great seating choices
Link.
http://www.literacylovescompany.com/2016/04/flexible-classroom-seating.html

Figure A65. Resource-Classroom resource5
Description. Progress Monitoring for IEPs and RTI made easy FREE editable and easy to use Progress Rings to help save you time and paper Blog post and instructions at Mrs Ds Corner
Link.
http://www.mrsdscorner.com/2015/07/ProgressMonitoringMadeQuickEasy.html

Figure A66. Resource-Reading8
Description. One Stop Teacher Shop Free Resources for NonFiction Texts and free center response sheets

Link.
http://www.onestopteachershop.com/2014/12/free-resources-for-non-fiction-texts.html

Figure A67. Resource-Back-to-school3
Description. Ice breaking activities for the first few days of school to help build a community atmosphere

Link.
http://www.scholastic.com/teachers/top-teaching/2013/09/building-classroom-community?eml=Teachers/e/20130912/Facebook///SMO/Teachers/TopTeaching/KrisciaCabral/

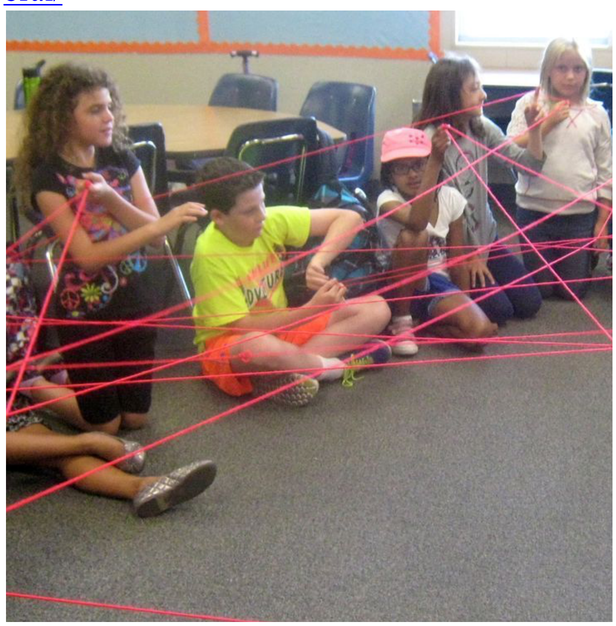


Figure A68. Resource-Back-to-school4
Description. Free Classroom Decor Free Back to School Free Labels Editable LabelsHi teaching friends Here is an editable freebie for back to school so you can make any all labels you need for your classroom If you want the same font as the one in the example you will want to download KG Two is Better Than One If you use these I would super duper love your feedback as well
Link.
http://www.teacherspayteachers.com/Product/FREE-Classroom-Decor-Labels-Editable-Black-and-White-Options-2650878

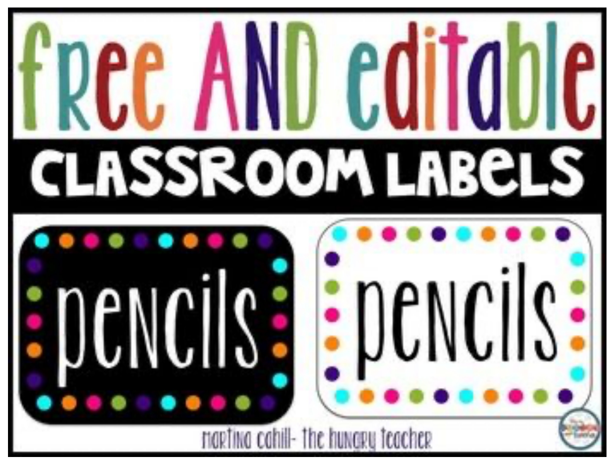


Figure A69. Resource-Growth mindset16
Description. Looking to help build a growth mindset in your students This interactive minibook freebie will help you outIt is a noneditable PDF Thank you for your interestCheck out my store I love creating products with building growth mindset independence in mindReading WorkshopWriting WorkshopMath Skills PracticeIntegrated Sight Words Math Practice
Link.
http://www.teacherspayteachers.com/Product/Growth-Mindset-Interactive-Mini-Book-Freebie--2598085

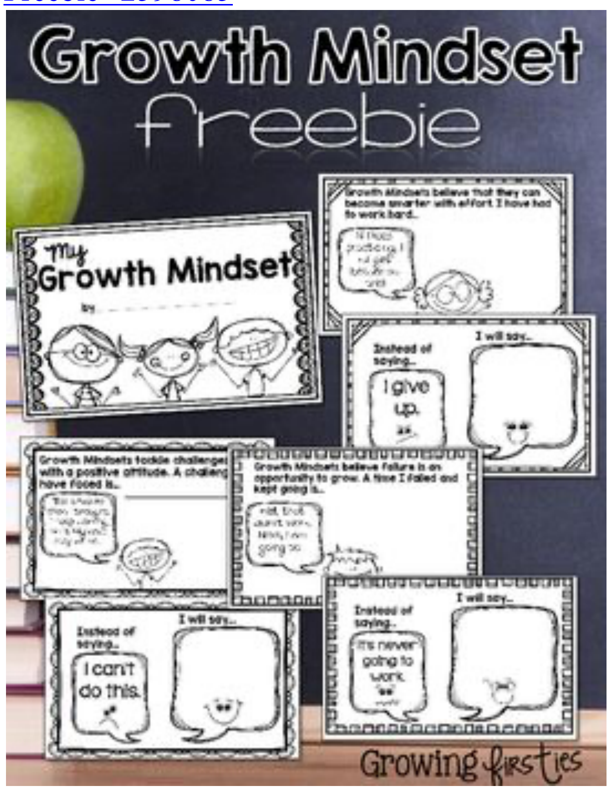


Figure A70. Resource-Spelling1
Description. Heres a FREE Spellers Choice Menu that can be used with any spelling list The kids love it because theres a variety of activities to choose from and teachers love it because these activities manage to incorporate phonics grammar writing AND math I just place it in a sheet protector in their takehome binder for them to use with homework every night

Link.
http://www.teacherspayteachers.com/Product/Spellers-Choice-Menu-1651903

Figure A71. Resource-Reading10
Description. Taking the Rocket Science out of Close Reading

Link.
http://www.theclassroomkey.com/2014/12/taking-the-rocket-science-out-of-close-reading.html

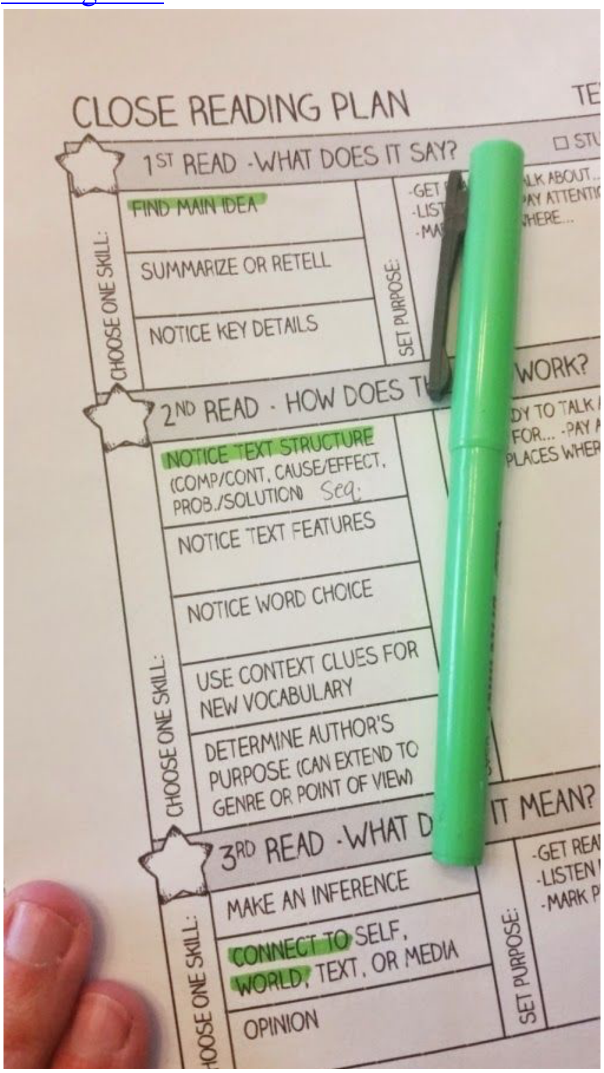


Figure A72. Resource-Spelling3
Description. These free printable spelling dictionaries are AMAZING, 6 different versions for kids ages 4-8. So perfect to use during writing workshop
Link.
http://www.themeasuredmom.com/printable-spelling-dictionary-for-kids/

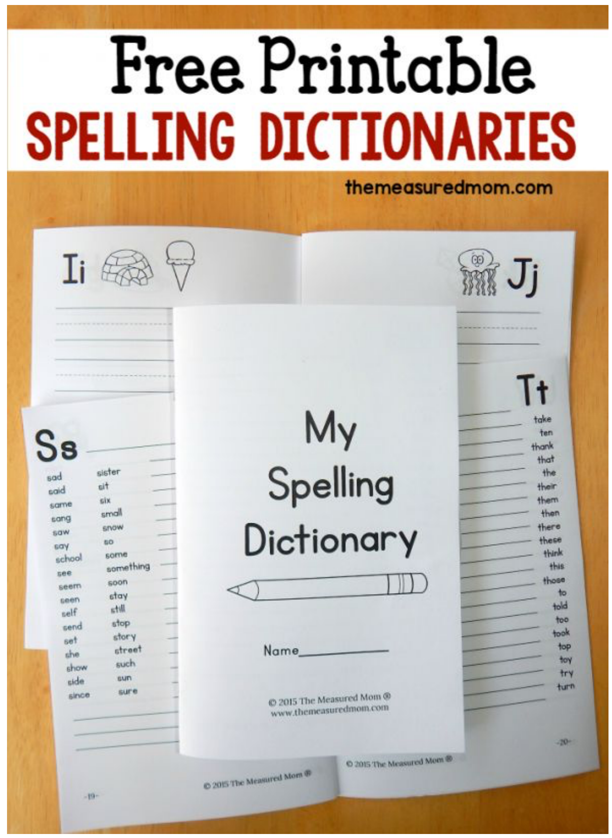


Figure A73. Resource-Classroom resource6
Description. Here is a photo tutorial on how to make privacy folders from dollar store

Link.
http://www.undercoverclassroom.com/2015/07/do-it-yourself-privacy-folders.html

Figure A74. Resource-Growth mindset12
Description. The Best TV/Movie Scenes Demonstrating A Growth Mindset. Help Me Find More. Larry Ferlazzos Websites of the Day
Link.
http://www.youtube.com/watch?v=AWtRadR4zYM

Figure A75. Resource-Classroom resource7
Description. Slide2
Link.
https://collaboratinginkinder.com/2017/03/23/how-to-make-worksheets-for-your-classroom-or-teacherpayteachers/

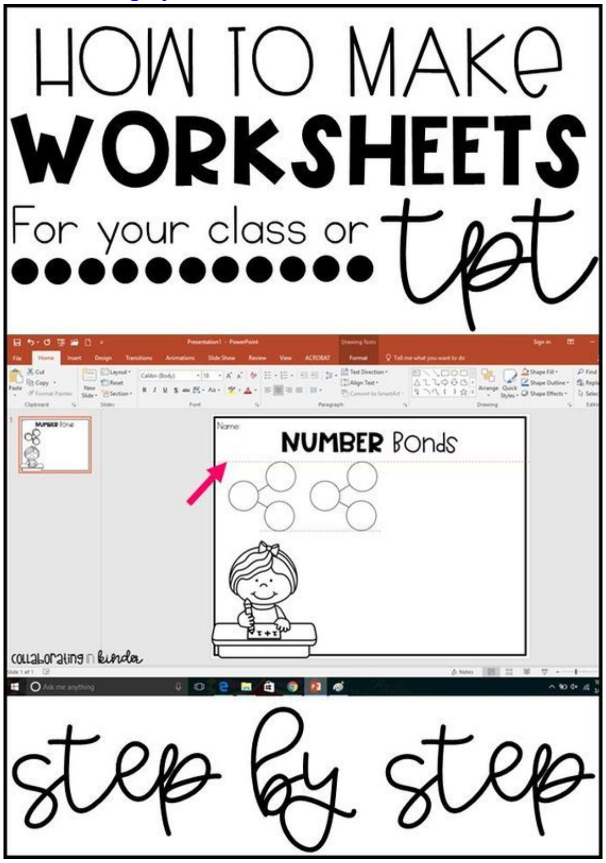


Figure A76. Resource-Growth mindset14
Description. Growth Mindset Bulletin Board
Link.
https://www.bloglovin.com/blogs/undercover-classroom-13667079/growth-mindset-bulletin-board-5110021553

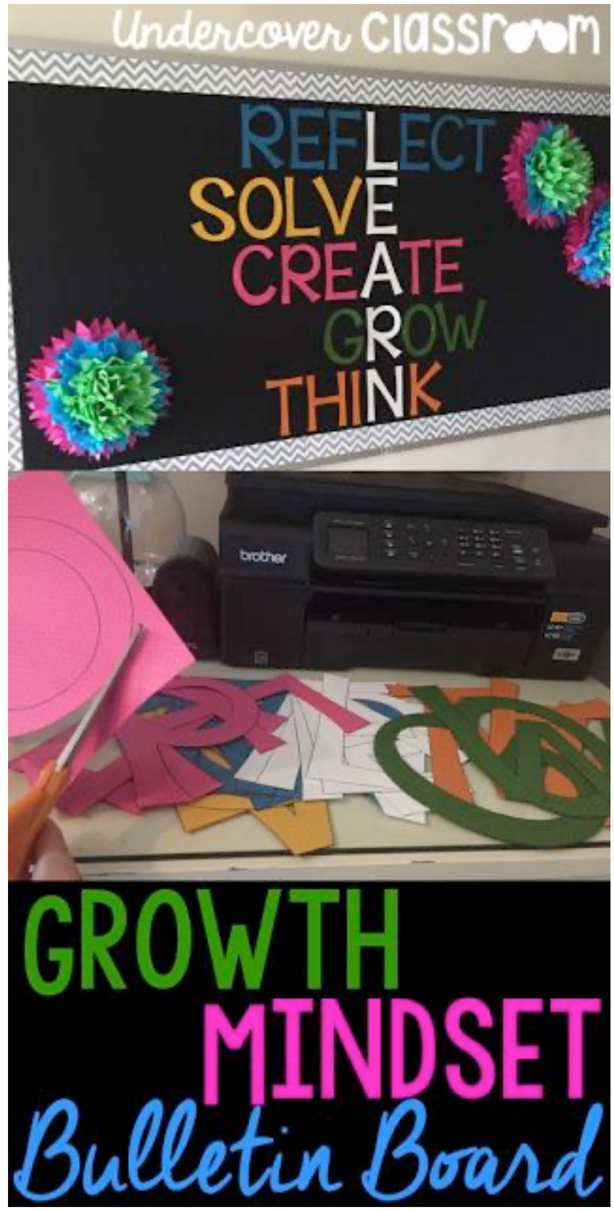


Figure A77. Resource-STEM challenge6
Description. Build a parachute for Santa a shelf for the elf and the tallest tree 3 Holiday Themed STEM Challenges for Elementary Students STEM Activities STEM Projects
Link.
https://www.teacherspayteachers.com/Product/December-STEM-3-Holiday-Themed-Challenges-2186805

Figure A78. Resource-Growth mindset15
Description. Growth Mindset Certificates FREE

Link.
https://www.teacherspayteachers.com/Product/Growth-Mindset-Certificates-FREE-2655228

Figure A79. Resource-Growth mindset13
Description. GROWTH MINDSET Great resource for introducing elementary students to positive selfspeak

Link.
https://www.teacherspayteachers.com/Product/Growth-Mindset-Posters-wStudent-Printables-2192346

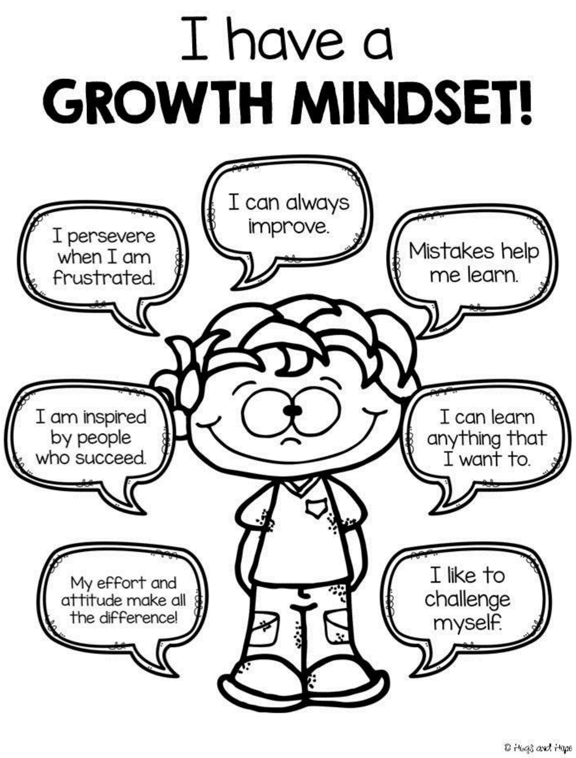
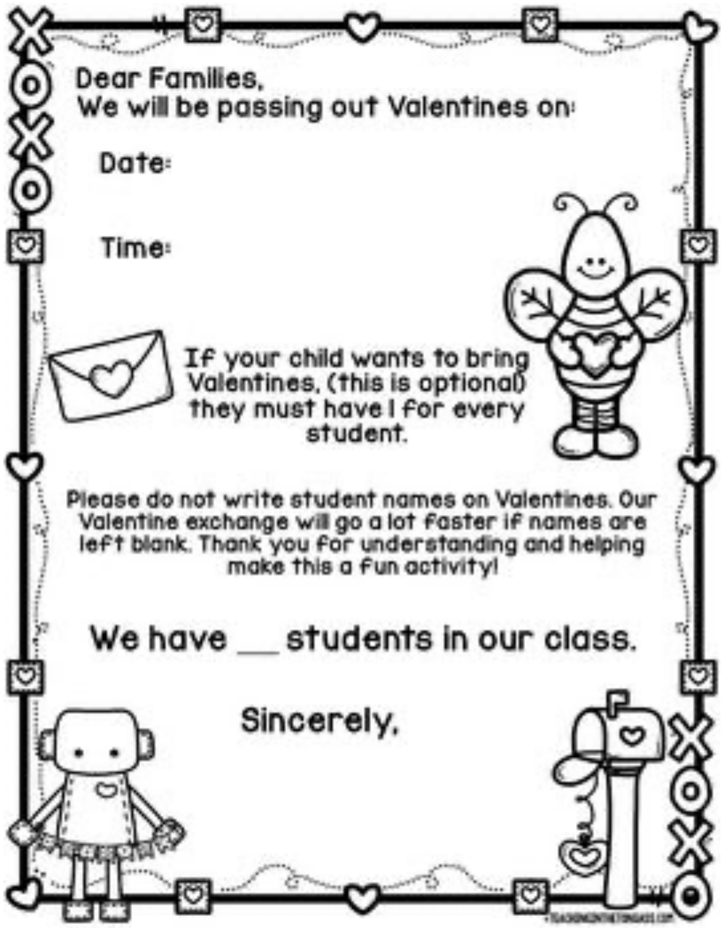


Figure A80. Resource-Reading9
Description. Get students thinking deeply about their reading A huge collection of response pages designed in an engaging notebook format Use individually or create customized readers notebook packets Use with virtually any piece of literature Differentiated at three levels Common Core aligned Perfect for guided reading book clubs and practicing key reading skills Gr 25
Link.
https://www.teacherspayteachers.com/Product/Readers-Notebook-Response-Pages-for-Literature-HALF-PAGE-SET-766284?pp=1

Figure A81. Resource-For parents3
Description. Valentine Parent Letter Free Editable
Link.
https://www.teacherspayteachers.com/Product/Valentine-Parent-Letter-Free-Editable-1100928


Dear Families,
We will be passing out Valentines on:

Date:

Time:

If your child wants to bring Valentines, (this is optional) they must have 1 for every student.

Please do not write student names on Valentines. Our Valentine exchange will go a lot faster if names are left blank. Thank you for understanding and helping make this a fun activity!

We have __ students in our class.

Sincerely,

APPENDIX B.

R Code for Latent Space Positions and Circle Plots

```
#load the packages
library(readxl)
library(amen)
library(network)
library(latentnet)
library(ergm)
library(statnet)
library(SciViews)
library(igraph)
library(intergraph)
library(data.table)
library(dplyr)

#set working directory
setwd("/Users/yuqingliu/Dropbox/Dissertation/Data/Processed data/")

#read in the data
data<-read_excel("weekly network data over 47 weeks.xlsx",sheet="Sheet1")

#create a container to store the results either as vector, matrix, or data frame
#store results from each iteration in the container outside the loop

#generate 47 listing numbers
my_list <- c(0:40,42:47)

#create 4 empty vectors - store the BIC in each of the 4 models with different latent space
dimensions from 47 weekly, cumulative network datasets

#create empty list
latent_position_d1_list <- list()
latent_position_d2_list <- list()
latent_position_d3_list <- list()
latent_position_d4_list <- list()
model_bic <- list()

#for loop
for (i in 1:length(my_list)){
	#subset 47 weekly, cumulative network datasets
	data_week_subset<-data[which(data$week<=i-1), c("username","link")]
	#turn edgelist to adjacency table
	data_week_contingency<-table(data_week_subset)
```

```
#turn adjacency table to adjacency matrix, table->data frame->matrix
data_week_matrix<-as.matrix(as.data.frame.matrix(data_week_contingency))
network <- as.network(data_week_matrix, matrix.type="adjacency", bipartite=T)

######grab the username and resource in the order of the network data, then turn them into
a vector for node names
user<-rownames(data_week_matrix)
resource<-colnames(data_week_matrix)
user.resource<-c(user, resource)
network.vertex.names(network) <- user.resource

#analyze
#lfm.fit<-ergmm(network ~ bilinear(d=2))
#assess model fit before extracting latent positions

lfm.fit.d1 <- ergmm(network ~ bilinear(d=1), control=ergmm.control(burnin=10000))
lfm.fit.d2 <- ergmm(network ~ bilinear(d=2), control=ergmm.control(burnin=10000))
lfm.fit.d3 <- ergmm(network ~ bilinear(d=3), control=ergmm.control(burnin=10000))
lfm.fit.d4 <- ergmm(network ~ bilinear(d=4), control=ergmm.control(burnin=10000))

#create a null vector
bic <- c()
#extract bic
bic[1]<-summary(lfm.fit.d1)$bic$overall
bic[2]<-summary(lfm.fit.d2)$bic$overall
bic[3]<-summary(lfm.fit.d3)$bic$overall
bic[4]<-summary(lfm.fit.d4)$bic$overall
print(bic)

week<-i-1
model_dimension<-c(1:4)
model_bic[[i]]<-data.frame(cbind(model_dimension, bic, week))
#note: turn vector into the data.frame before assigning them to model_bic outside of the
"for loops"

#to extract latent positions, I need the iteration number or the week number, and the node
name
latent_position_d1_list[[i]]<-data.frame( cbind( data.frame(summary(lfm.fit.d1)$mkl$Z),
user.resource, week)  )
latent_position_d2_list[[i]]<-data.frame( cbind( data.frame(summary(lfm.fit.d2)$mkl$Z),
user.resource, week)  )
latent_position_d3_list[[i]]<-data.frame( cbind( data.frame(summary(lfm.fit.d3)$mkl$Z),
user.resource, week)  )
latent_position_d4_list[[i]]<-data.frame( cbind( data.frame(summary(lfm.fit.d4)$mkl$Z),
user.resource, week)  )
```

```
	#extract MCMC diagnostics, 1.autocorrelation plot; 2.traceplot&posterior density
	#See if I have convergence in the MCMC
	setwd("~/Dropbox/Dissertation/Results/r output/MCMC Diagnostics/Dimension 1")
	pdf(paste0("MCMC Diagnostics week ",week," d1.pdf"))
	mcmc.diagnostics(lfm.fit.d1)

	setwd("~/Dropbox/Dissertation/Results/r output/MCMC Diagnostics/Dimension 2")
	pdf(paste0("MCMC Diagnostics week ",week," d2.pdf"))
	mcmc.diagnostics(lfm.fit.d2)

	setwd("~/Dropbox/Dissertation/Results/r output/MCMC Diagnostics/Dimension 3")
	pdf(paste0("MCMC Diagnostics week ",week," d3.pdf"))
	mcmc.diagnostics(lfm.fit.d3)

	setwd("~/Dropbox/Dissertation/Results/r output/MCMC Diagnostics/Dimension 4")
	pdf(paste0("MCMC Diagnostics week ",week," d4.pdf"))
	mcmc.diagnostics(lfm.fit.d4)
	#clear off the dev.list() if it is not empty, which is R's inner place to store all the plots in this
session
	while (!is.null(dev.list()))  dev.off()
	print(dev.list())
	#close off the pdf file generating process
}

#based on a list of generated data frames, append them all and generate an overall data file
df.bic <- rbindlist(model_bic)
df.latent.position.d1 <- rbindlist(latent_position_d1_list)
df.latent.position.d2 <- rbindlist(latent_position_d2_list)
df.latent.position.d3 <- rbindlist(latent_position_d3_list)
df.latent.position.d4 <- rbindlist(latent_position_d4_list)

#note: for each week of the network, select the best fitting model of a specified dimension with
minimum BIC
#extract MCMC diagnostics to evaluate MCMC convergence
#latent positions

#clean BIC
library(dplyr)

# in dplyr pipes, mutate = create a new variable, group_by = within a group, filter = subset data,
select = keep selected variables.
min.BIC <- df.bic %>%
	group_by(week) %>%
	mutate(min_BIC = min(bic)) %>%
	mutate(minBIC_indicator = case_when(min_BIC==bic ~ 1,
	                                    min_BIC!=bic ~ 0,
```

```
                                   TRUE ~ NA_real_))
#subset data, only keep the models from each week with a minimum bic
min.BIC.model.dimension <- min.BIC %>%
      filter(minBIC_indicator==1) %>%
      select(week, model_dimension) %>%
      arrange(week)

#post-latent position analysis results cleaning
df.latent.position.final<-df.latent.position.d2 %>%
            mutate(week2 = case_when(week<=40 ~ week,
                                     week>=41 ~ week+1,
                                     TRUE ~ NA_real_)) %>%
            select(-week) %>%
            rename(week=week2, z1=X1, z2=X2)

########output latent factor model results########
setwd("/Users/yuqingliu/Dropbox/Dissertation/Data/Processed data")
library(foreign)
write.csv(df.latent.position.final,"weekly latent position estimates 060322.csv", row.names =
FALSE)


############second part################
#create circle plots
library(amen)
library(tidyverse)
library(stringr)
par(mar = c(1, 1, 1, 1))

setwd("/Users/yuqingliu/Dropbox/Dissertation/Data/Processed data/")
#load the latent position data
load("/Users/yuqingliu/Dropbox/Dissertation/Code/R/dissertation R.RData")
#read in the original teacher-resource two-mode network data
data<-read_excel("/Users/yuqingliu/Dropbox/Dissertation/Data/Processed data/weekly network
data over 47 weeks.xlsx",sheet="Sheet1")

#node labels
teacher<-data[, c("username","userid")]
teacher<-unique(teacher)
resource<-data[,c("link", "resource_category_label")]
resource<-unique(resource)

#in the latent position data, create an indicator to indicate if the node is a resource or a teacher
rspattern<-"http"
df.latent.position.final$rs_indi<-str_detect(df.latent.position.final[['user.resource']], rspattern)
df.latent.position.final$rs_indi<-as.integer(df.latent.position.final$rs_indi)
```

```
#no new tie added in week 41, so the cumulative weekly network at 41 = week 40, append week
41 to the data frame
week41 <- df.latent.position.final %>% filter(week==40) %>% mutate(week=week+1)
df.latent.position.v2 <- rbind(df.latent.position.final, week41) %>% arrange(week)

#generate plot titles
plot_title<-df.latent.position.v2 %>%
  select(week) %>%
  distinct() %>%
  arrange() %>%
  mutate(title = case_when (week==0 ~ paste0("Week ",week," Network Circle Plot"),
                            week>0 ~ paste0("Week ",week," Cumulative Network Circle Plot"),
                            TRUE ~ NA_character_) )
plot_title<-pull(plot_title, title)

#set the directory path for the circle plot
setwd("~/Dropbox/Dissertation/Results/R latent space model/circle plot")
pdf("circle plot with title.pdf", width = 9, height = 6)

#for teachers' latent position data, merge in the label of teachers' nodes
teacher.latent.position<- df.latent.position.v2 %>%
  filter(rs_indi==0) %>%
  select(-rs_indi) %>%
  rename(username=user.resource) %>%
  left_join(y=teacher, by=c("username"))

#for resources' latent position data, merge in the label of resources' nodes
resource.latent.position<- df.latent.position.v2 %>%
  filter(rs_indi==1) %>%
  select(-rs_indi) %>%
  rename(link=user.resource) %>%
left_join(y=resource, by=c("link"))

#the loop to generate 48 cumulative, weekly teacher-resource network circle plots
my_list <- c(0:47)
for (i in 1:length(my_list)) {
  #part 1. estimated latent positions
  #note the latent positions are already based on network data accumulated up to the given week,
week==i-1 is the right one
  #sort latent positions of teachers by userid; sort latent positions of resources by
resource_category_label
  #teacher.U is the row/sender factor to enter in the circle plot; resource.V the column/receiver
factor
  teacher.U<-teacher.latent.position %>% filter(week==i-1) %>% arrange(userid) %>%
select(z1,z2)
  teacher.U<-data.matrix(teacher.U)
```

```
  resource.V<-resource.latent.position %>% filter(week==i-1) %>%
arrange(resource_category_label) %>% select(z1,z2)
  resource.V<-data.matrix(resource.V)
  #(doesn't help much) add the number of teachers and resource together, later used to scale the
plot for better visualization
  #nodes <- dim(teacher.U)[1] + dim(resource.V)[1]

  #part 2. original network adjacency matrix
  data2<-data[which(data$week<=i-1), c("userid","resource_category_label")]
  #task: tidy up data2 based on whether the node has latent positions, using right_join
  #first, grab teachers and resources that have latent positions at a given week
  t.w.position<-teacher.latent.position %>% filter(week==i-1) %>% arrange(userid) %>%
select(userid)
  r.w.position<-resource.latent.position %>% filter(week==i-1) %>%
arrange(resource_category_label) %>% select(resource_category_label)
  #second, merge with data2 to only keep teachers and resources with estimated latent positions
  data2<- data2 %>%
    right_join(y=t.w.position, by=c("userid")) %>%
    right_join(y=r.w.position, by=c("resource_category_label"))

  #turn network edgelist to adjacency matrix
  data2 <- table(data2)
  class(data2)<-"matrix"

  #plot
  circplot(data2,
        U = teacher.U,
        V = resource.V,
        row.names = rownames(data2),
        col.names = colnames(data2),
        plotnames=TRUE,
        lcol = "dark gray",
        bty="u",
        #vscale=0.9,
        #pscale=1.75,mscale=0.5,
        #jitter = 0.1 * (nodes)/(1 + nodes),
        )
#add in the plot title
  title(main=paste0(plot_title[i]), cex.sub=2)
}

while (!is.null(dev.list()))  dev.off()
print(dev.list())
```

APPENDIX C.

Circle Plots of Latent Positions for Each of the 48 Cumulative, Weekly Networks

Figure C1. Week Zero Network Circle Plot

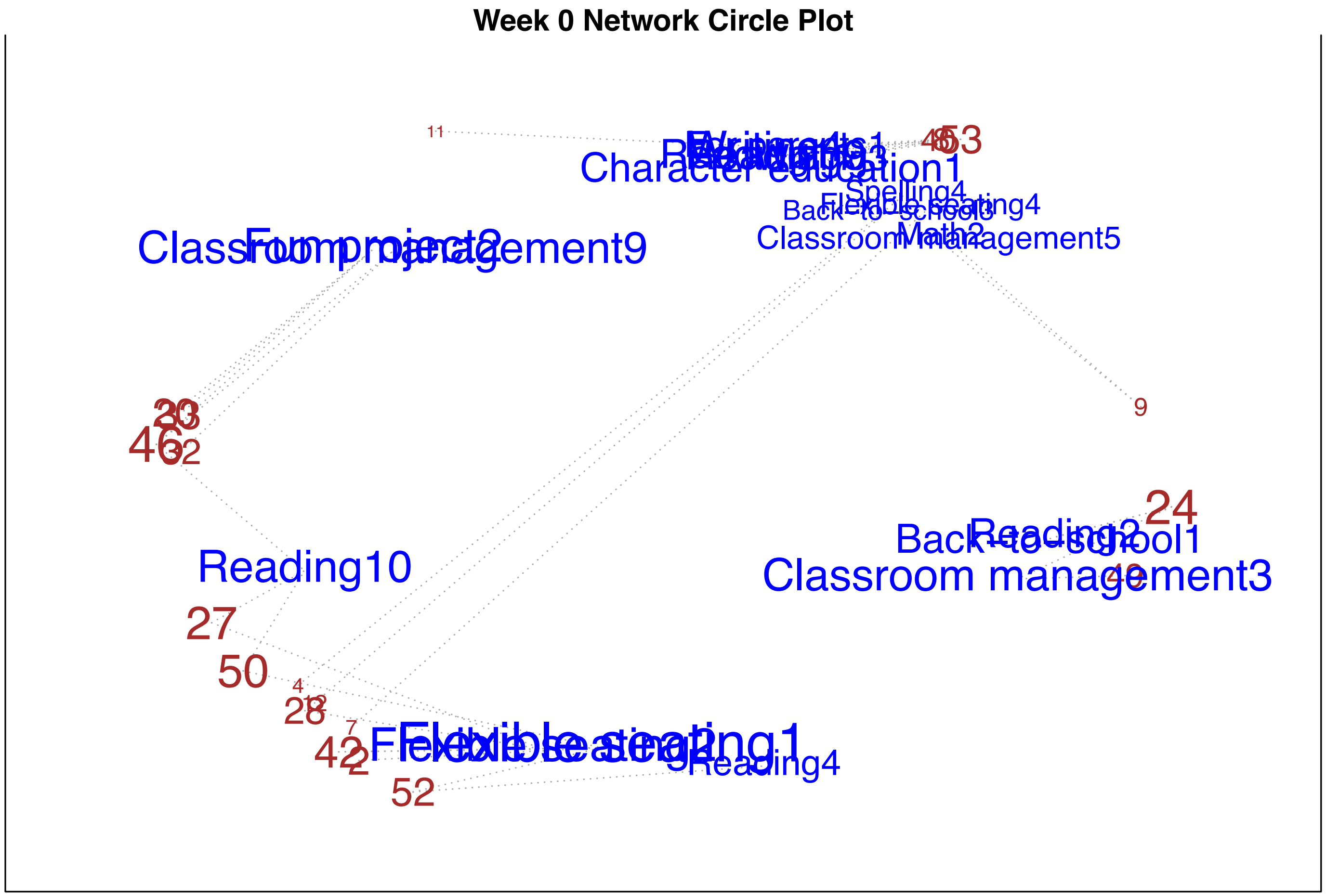


Figure C2. Week One Cumulative Network Circle Plot

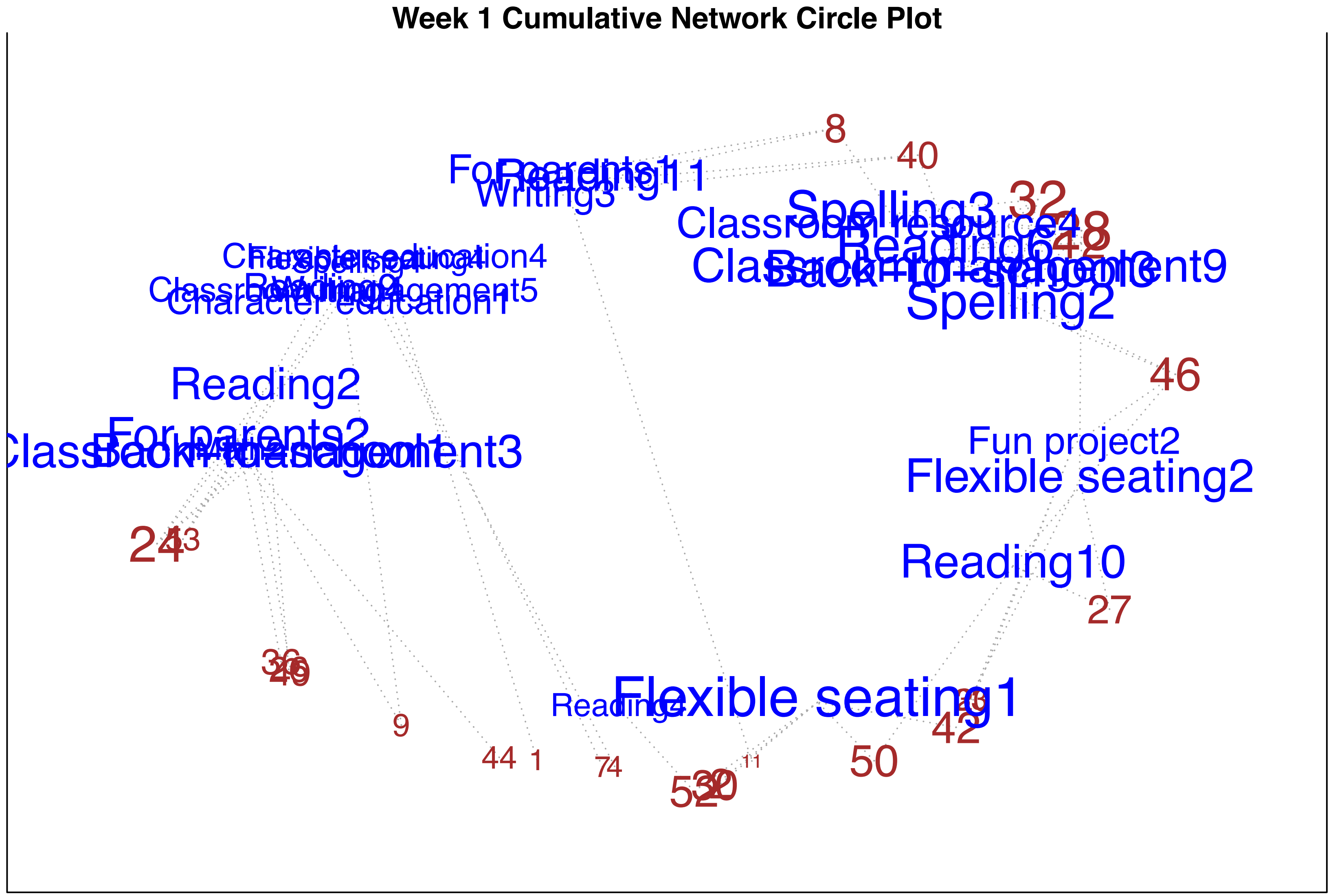


Figure C3. Week Two Cumulative Network Circle Plot

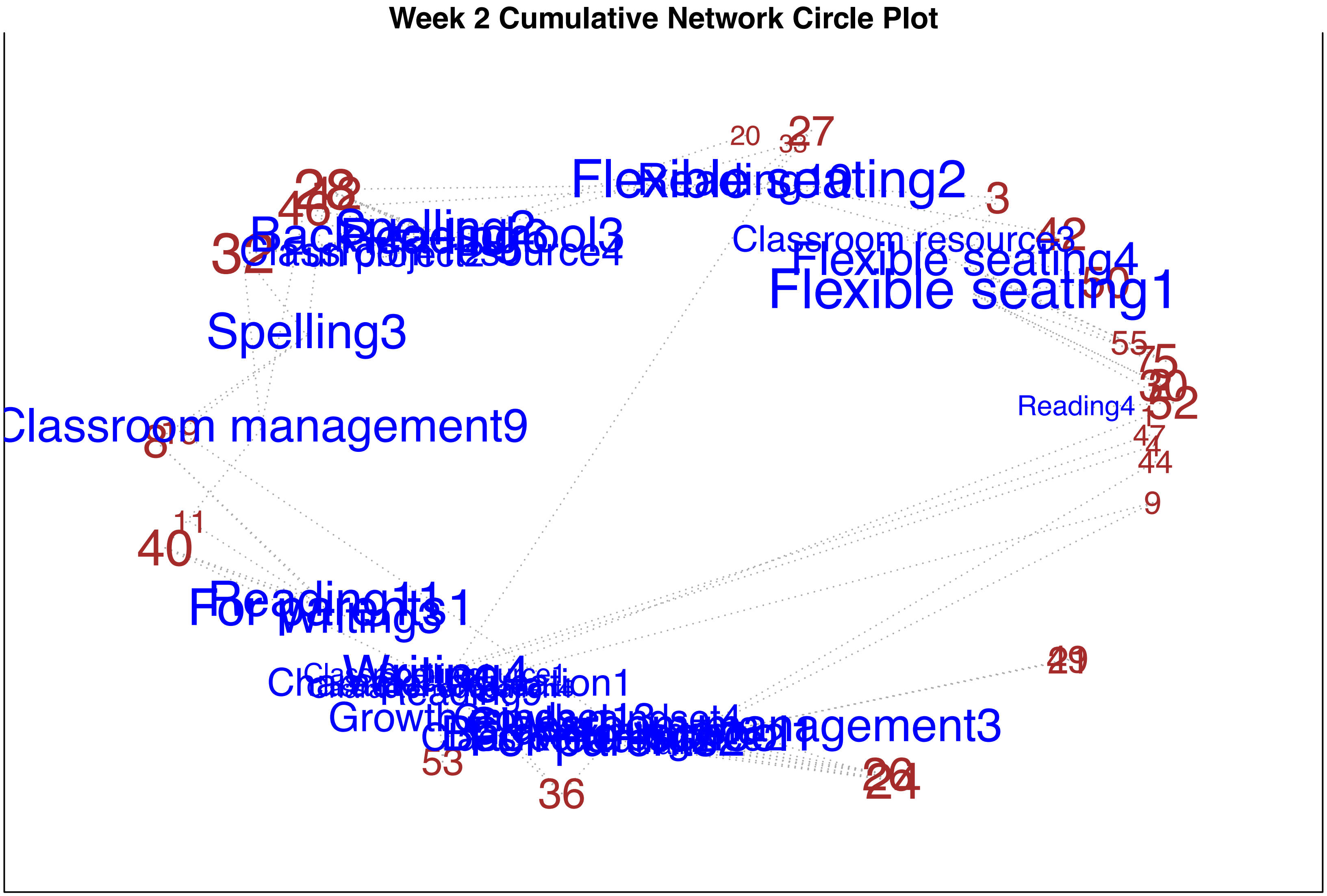


Figure C4. Week Four Cumulative Network Circle Plot

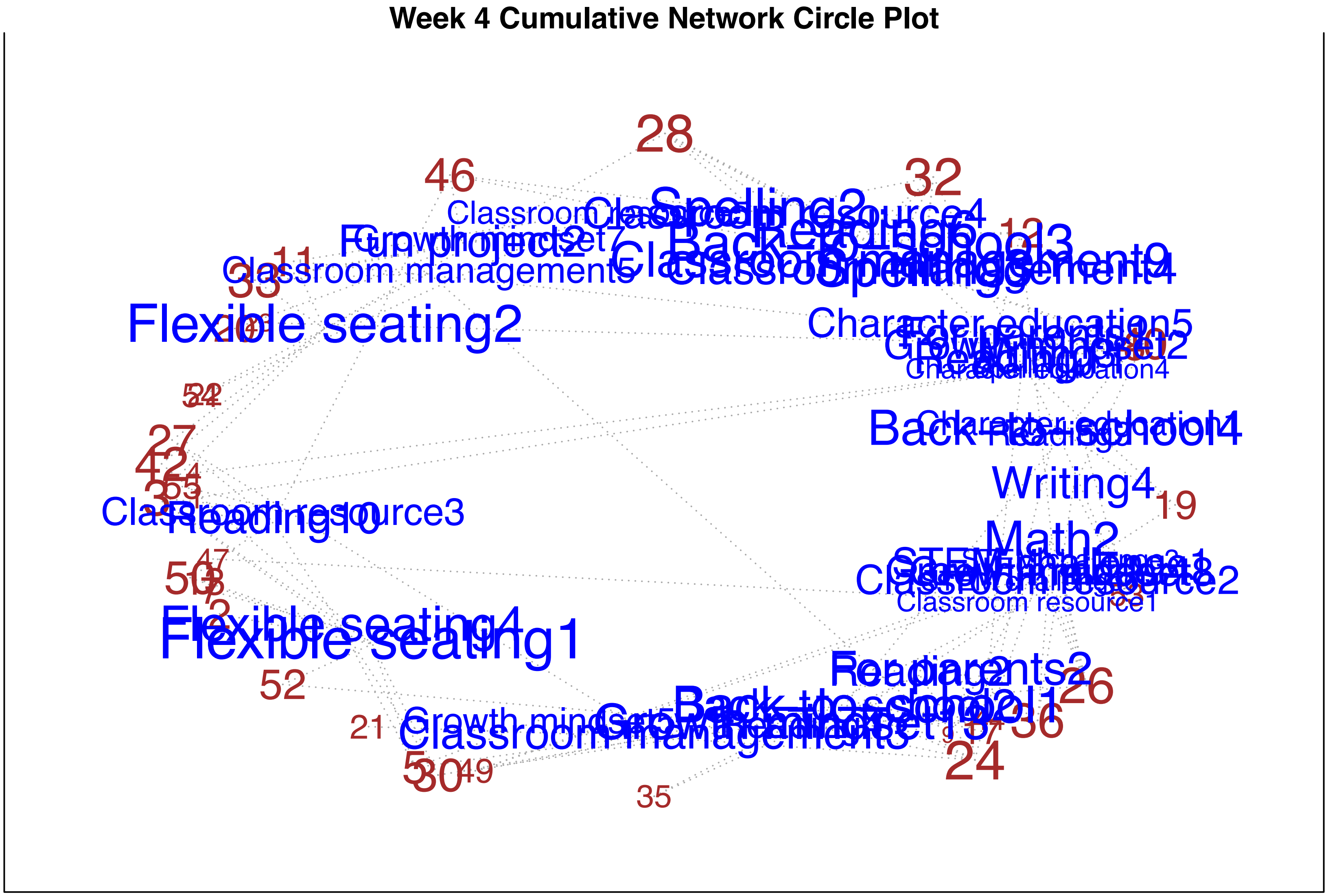


Figure C5. Week Five Cumulative Network Circle Plot

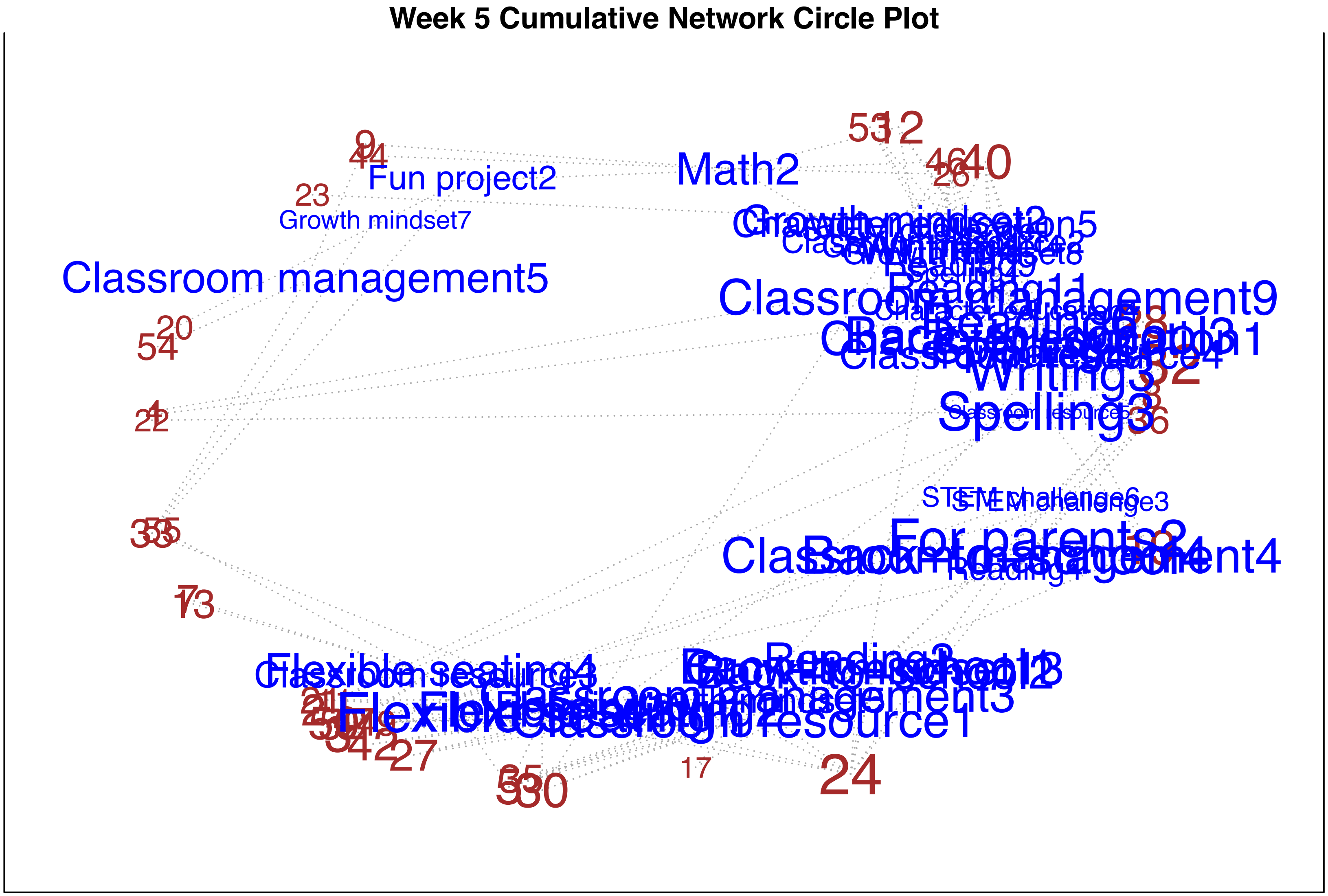


Figure C6. Week Six Cumulative Network Circle Plot

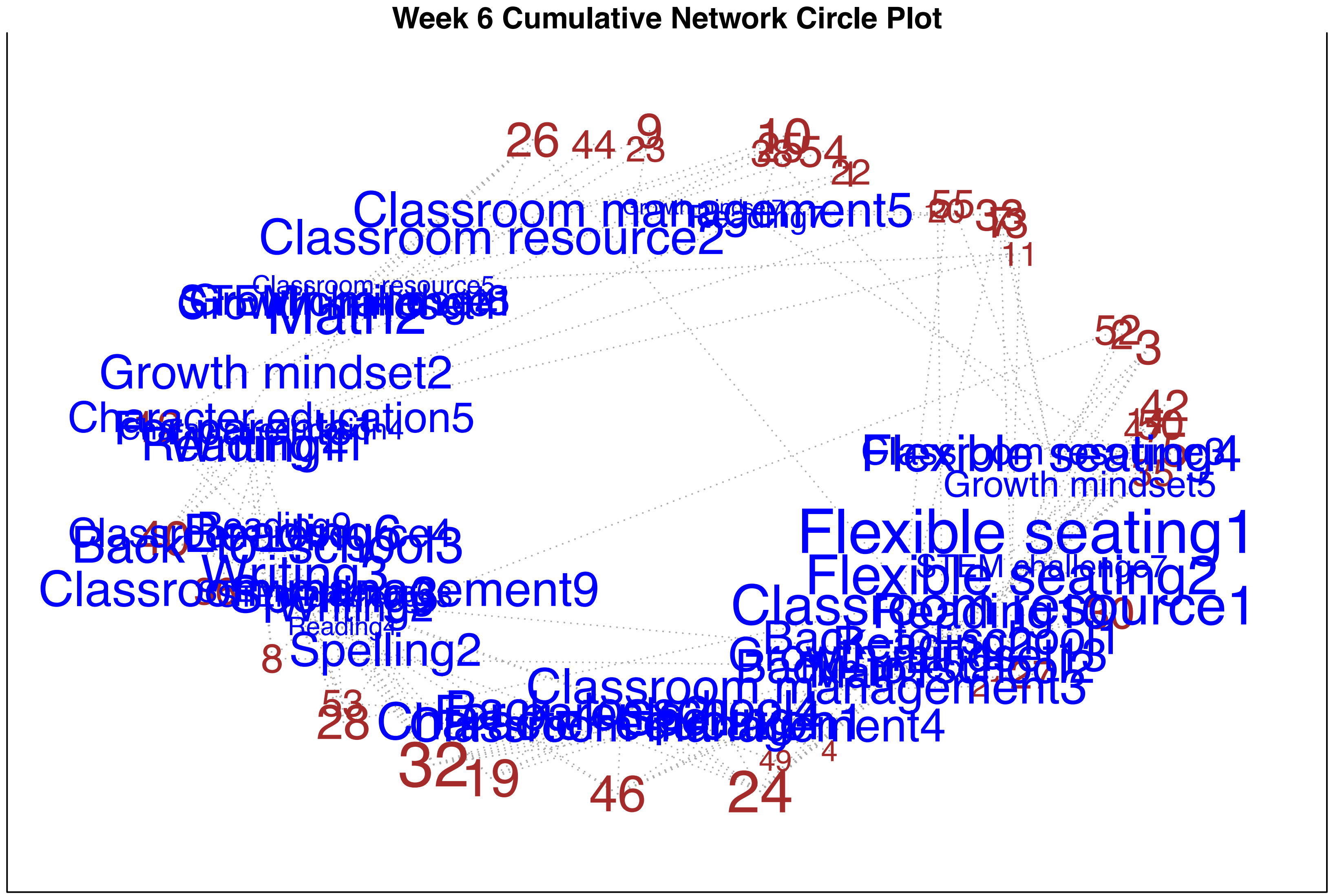


Figure C7. Week Seven Cumulative Network Circle Plot

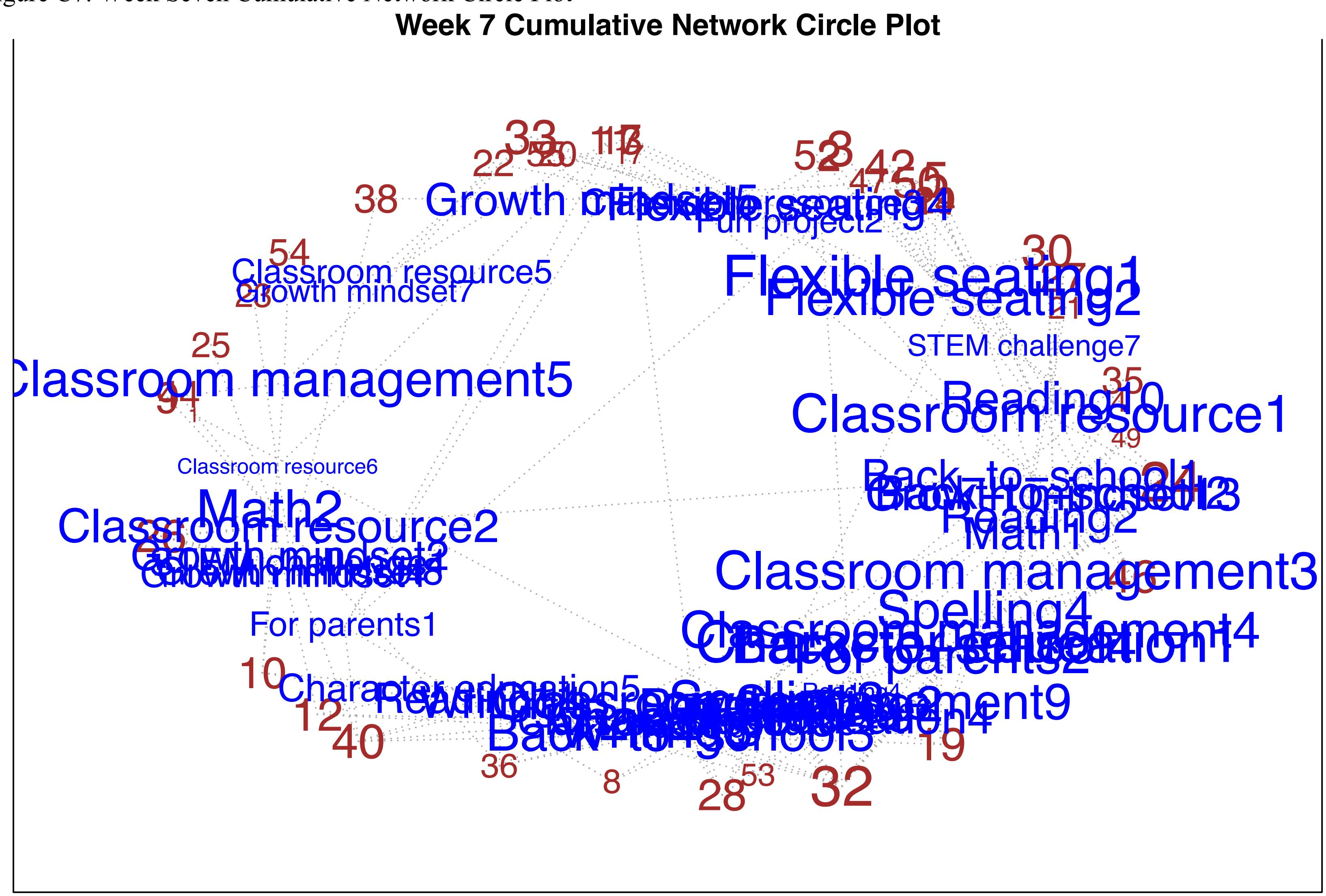


Figure C8. Week Eight Cumulative Network Circle Plot

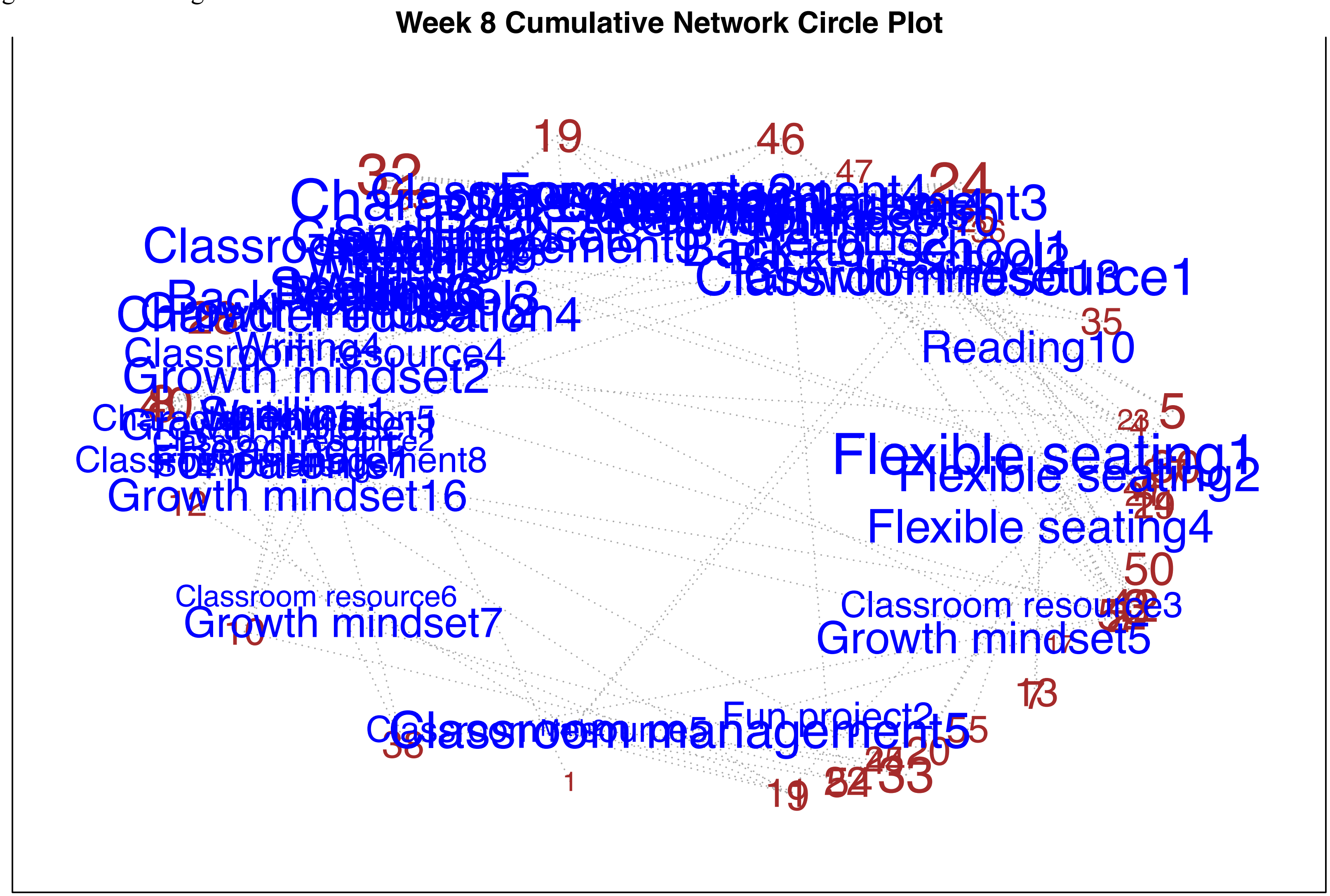


Figure C9. Week Nine Cumulative Network Circle Plot

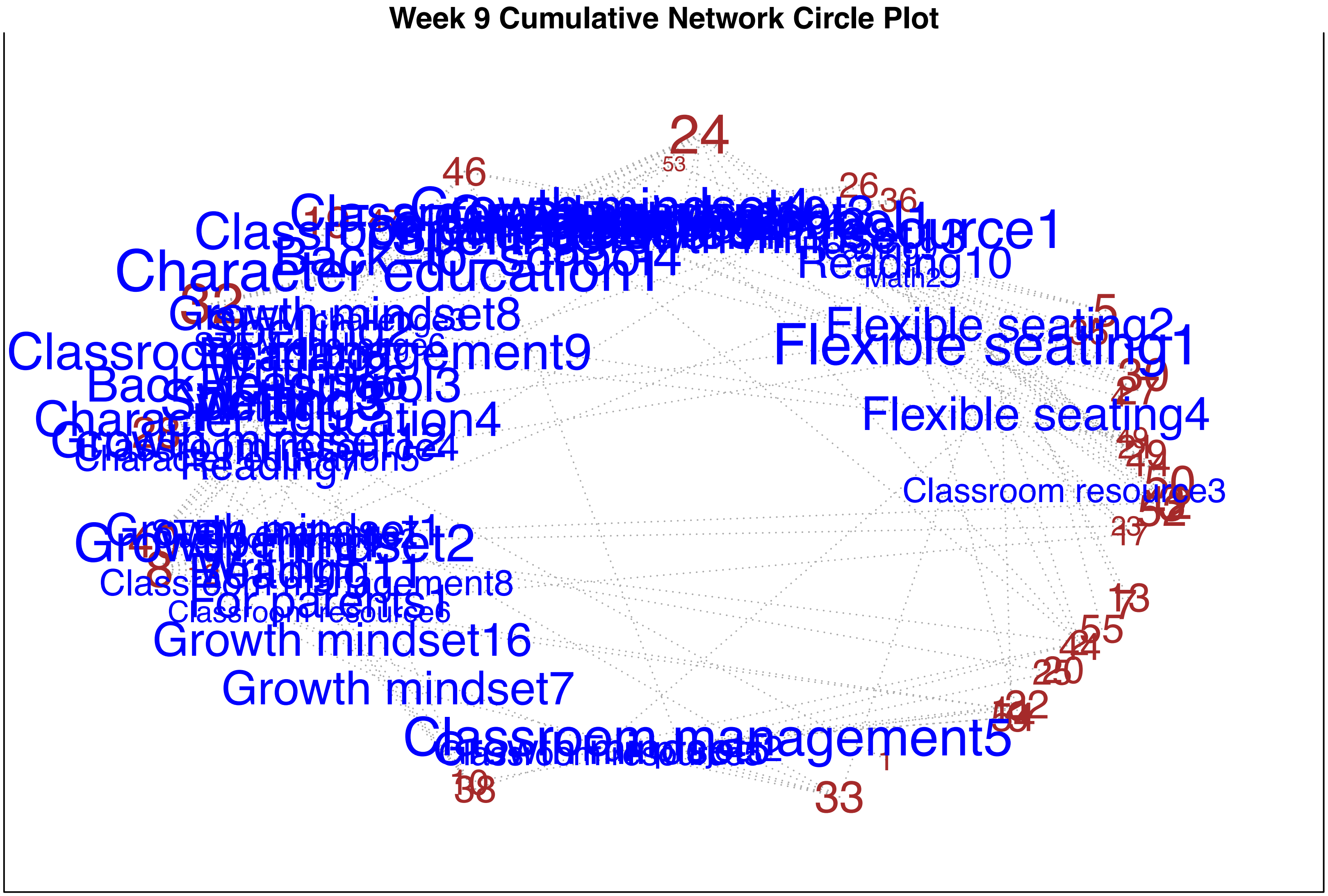


Figure C10. Week 10 Cumulative Network Circle Plot

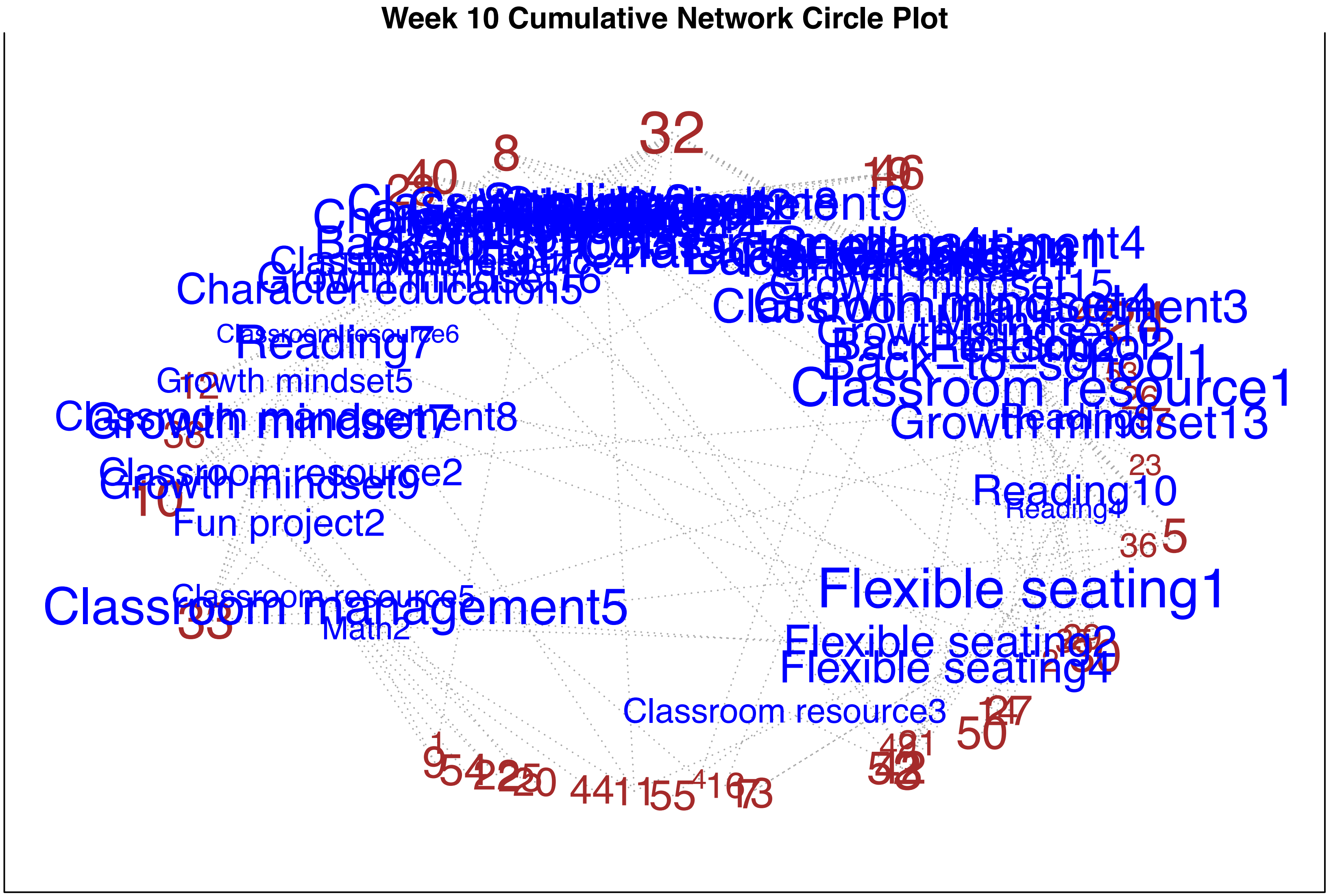


Figure C11. Week 11 Cumulative Network Circle Plot

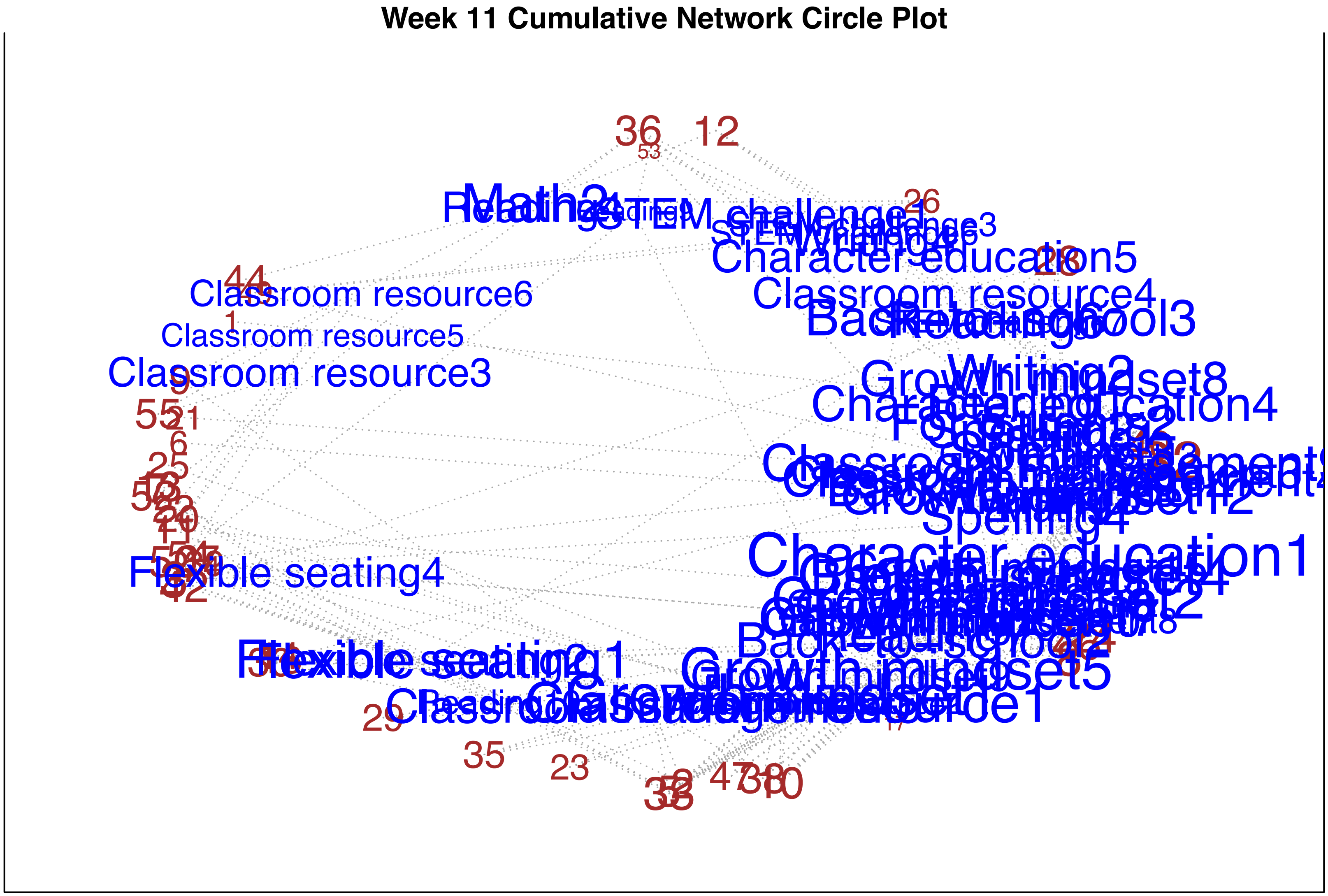


Figure C12. Week 12 Cumulative Network Circle Plot

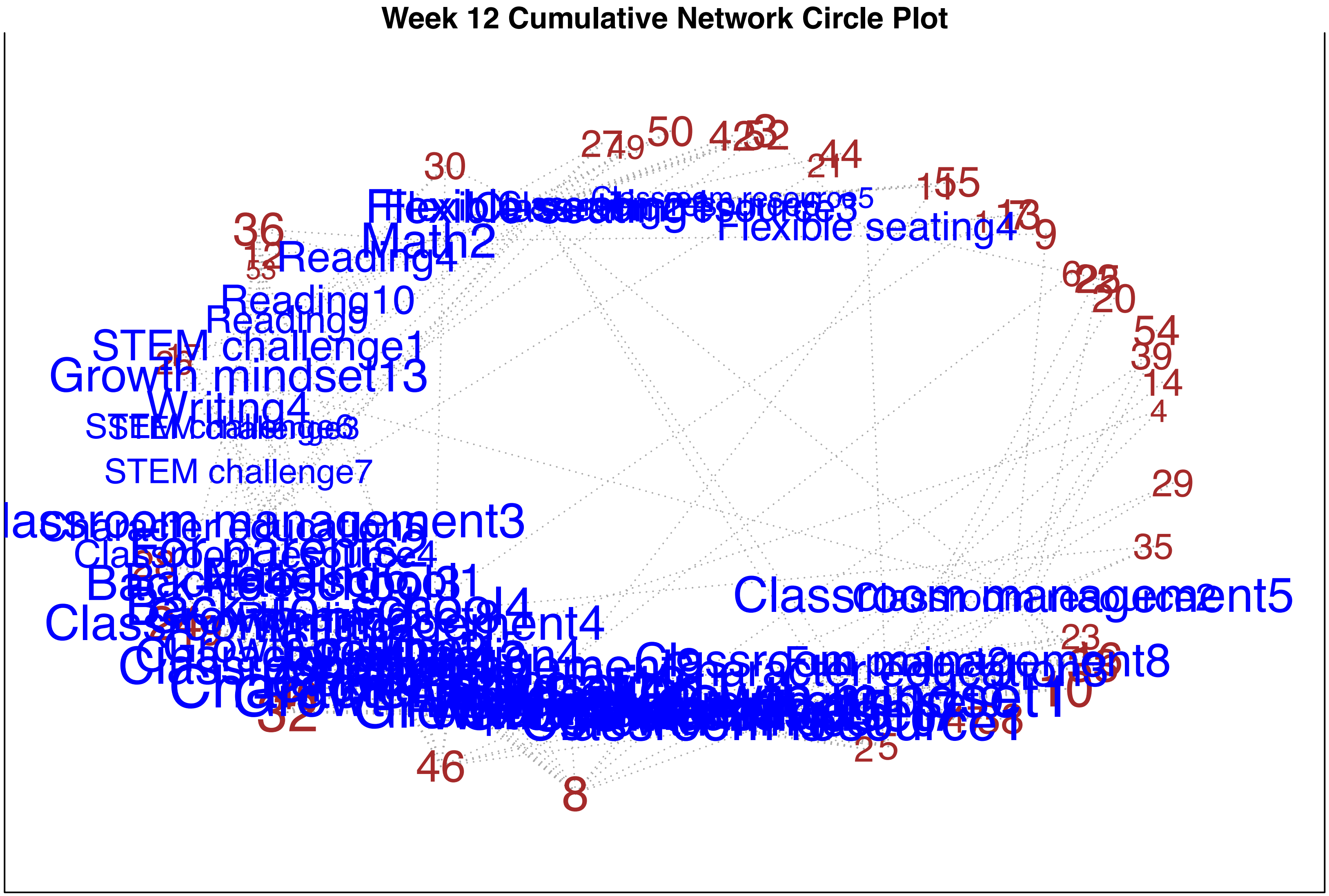


Figure C13. Week 13 Cumulative Network Circle Plot

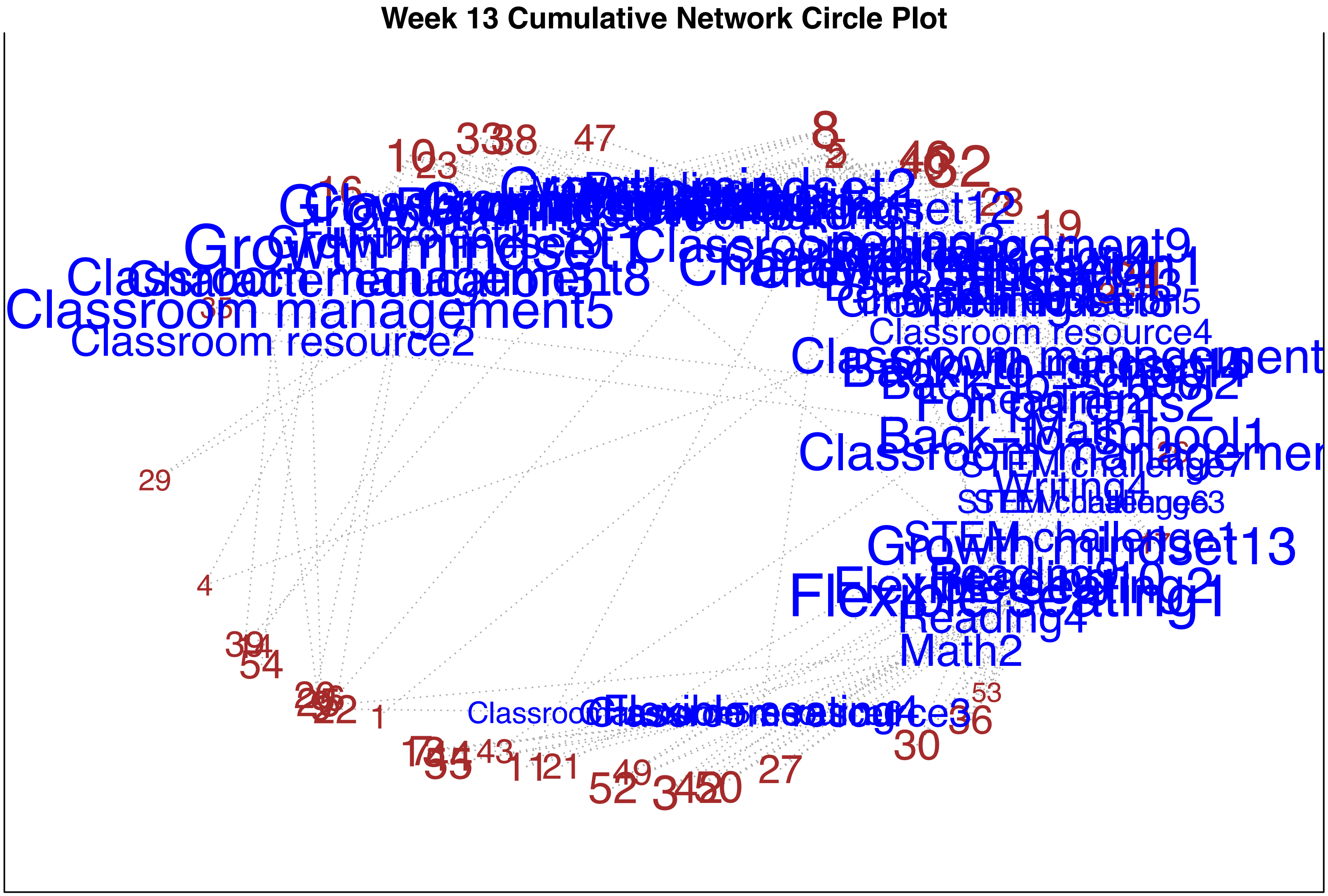


Figure C14. Week 14 Cumulative Network Circle Plot

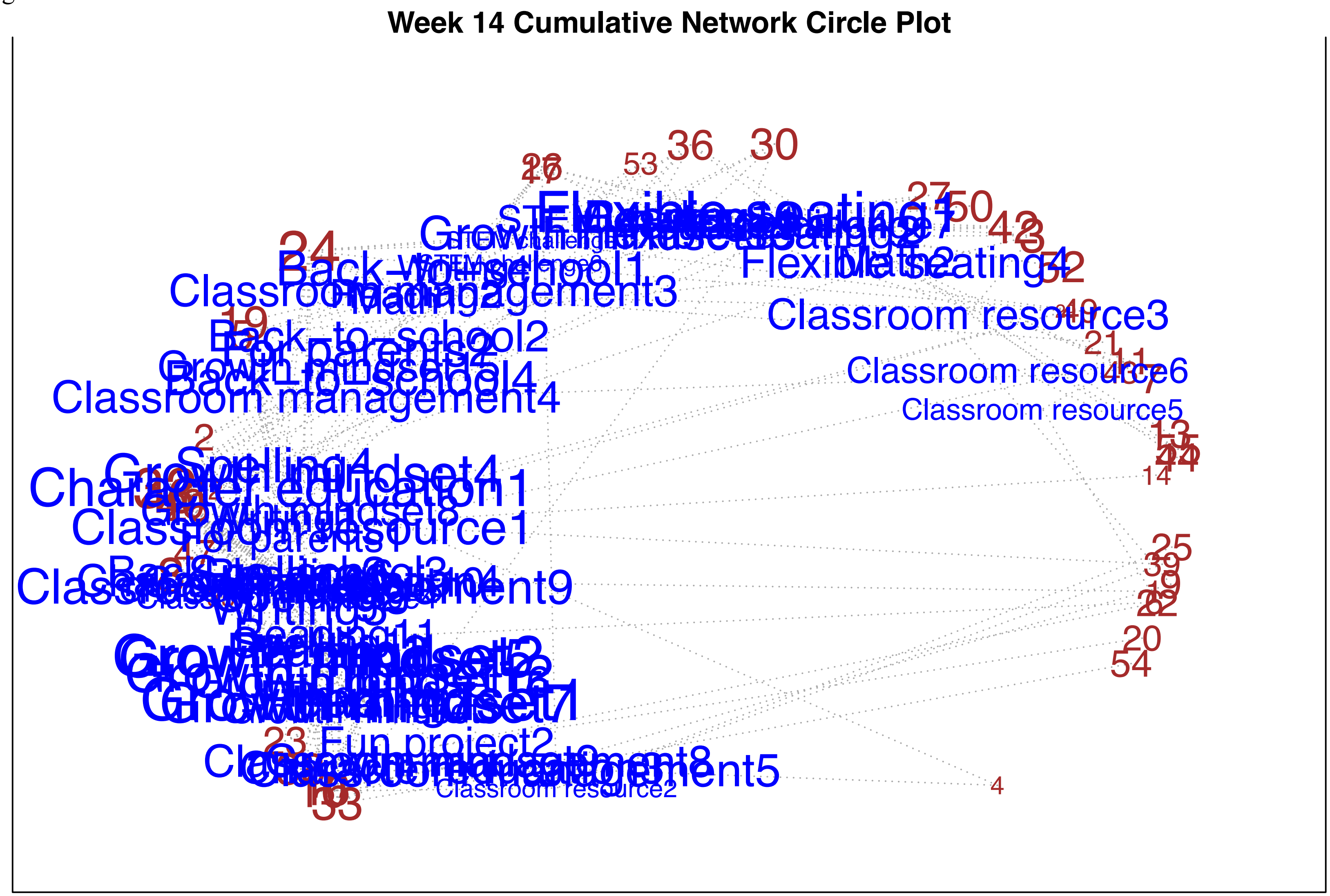


Figure C15. Week 15 Cumulative Network Circle Plot

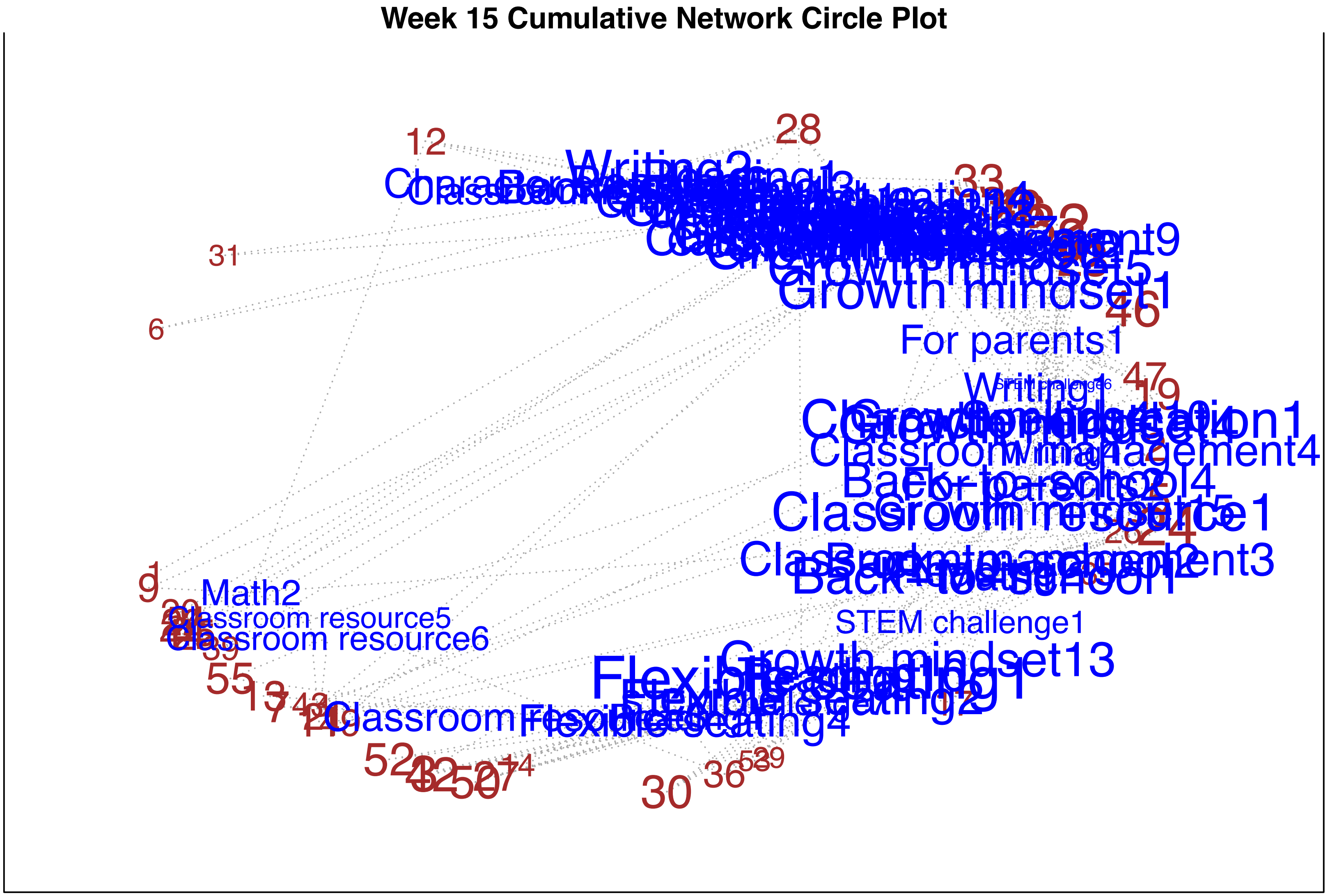


Figure C16. Week 16 Cumulative Network Circle Plot

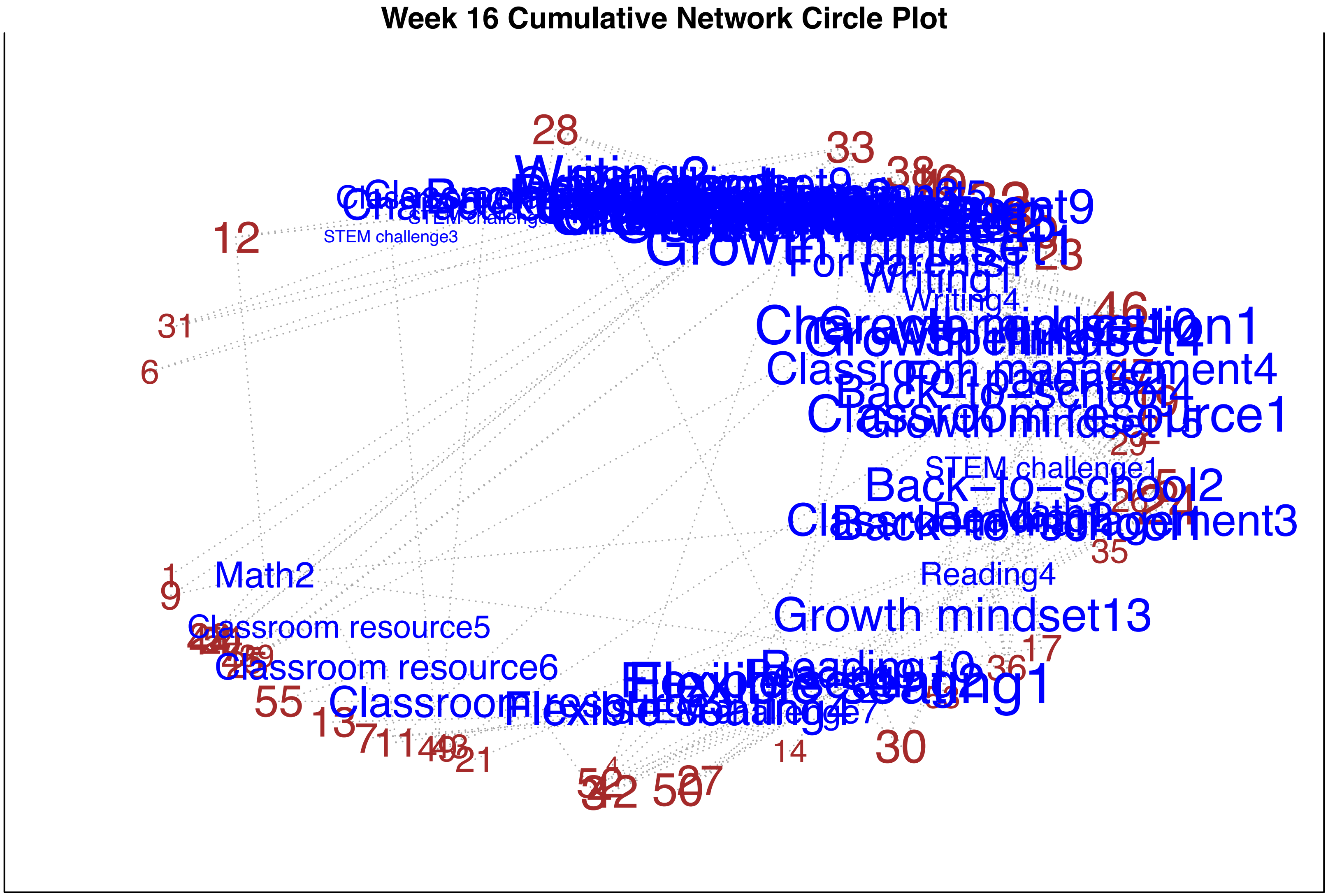


Figure C17. Week 17 Cumulative Network Circle Plot

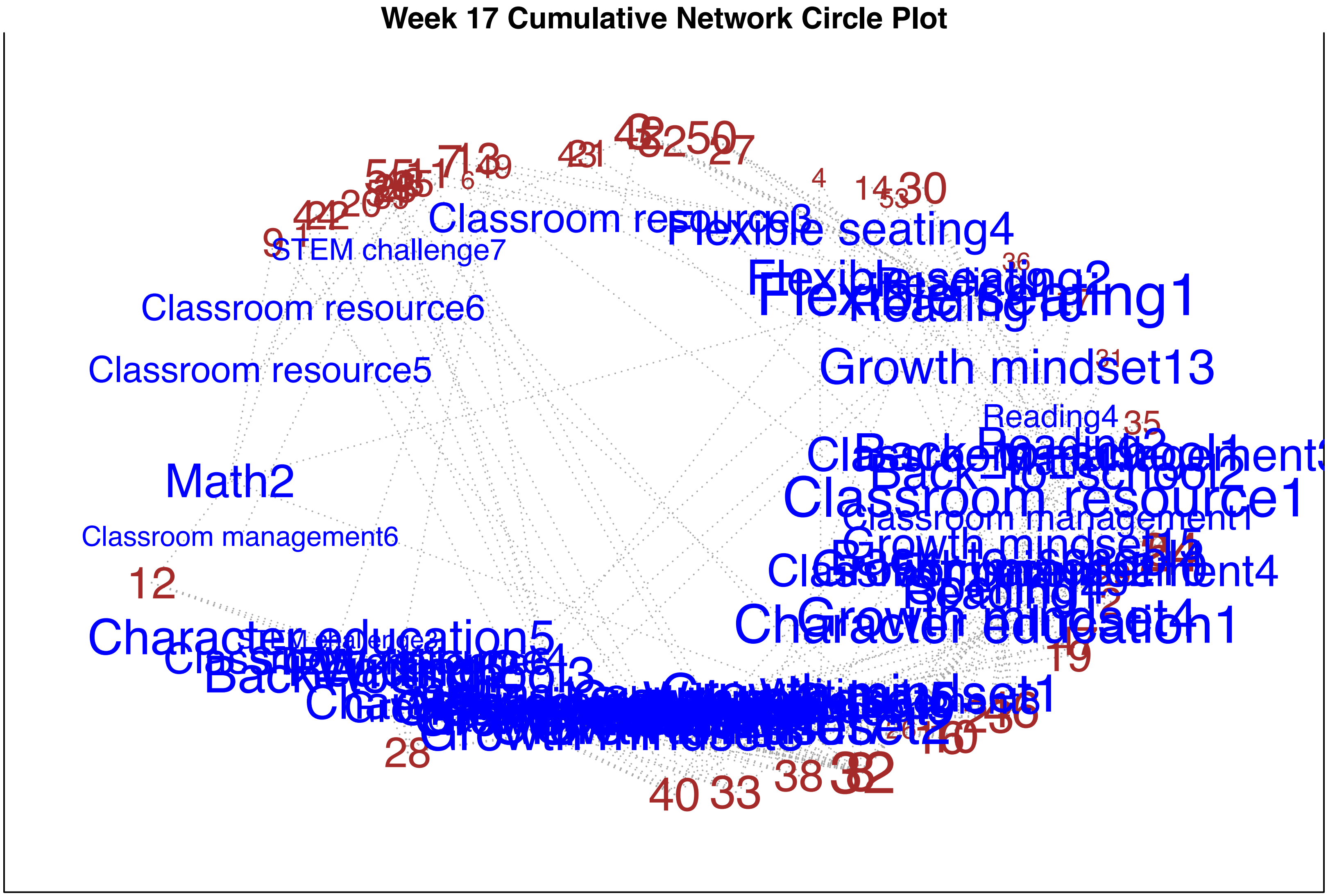


Figure C18. Week 18 Cumulative Network Circle Plot

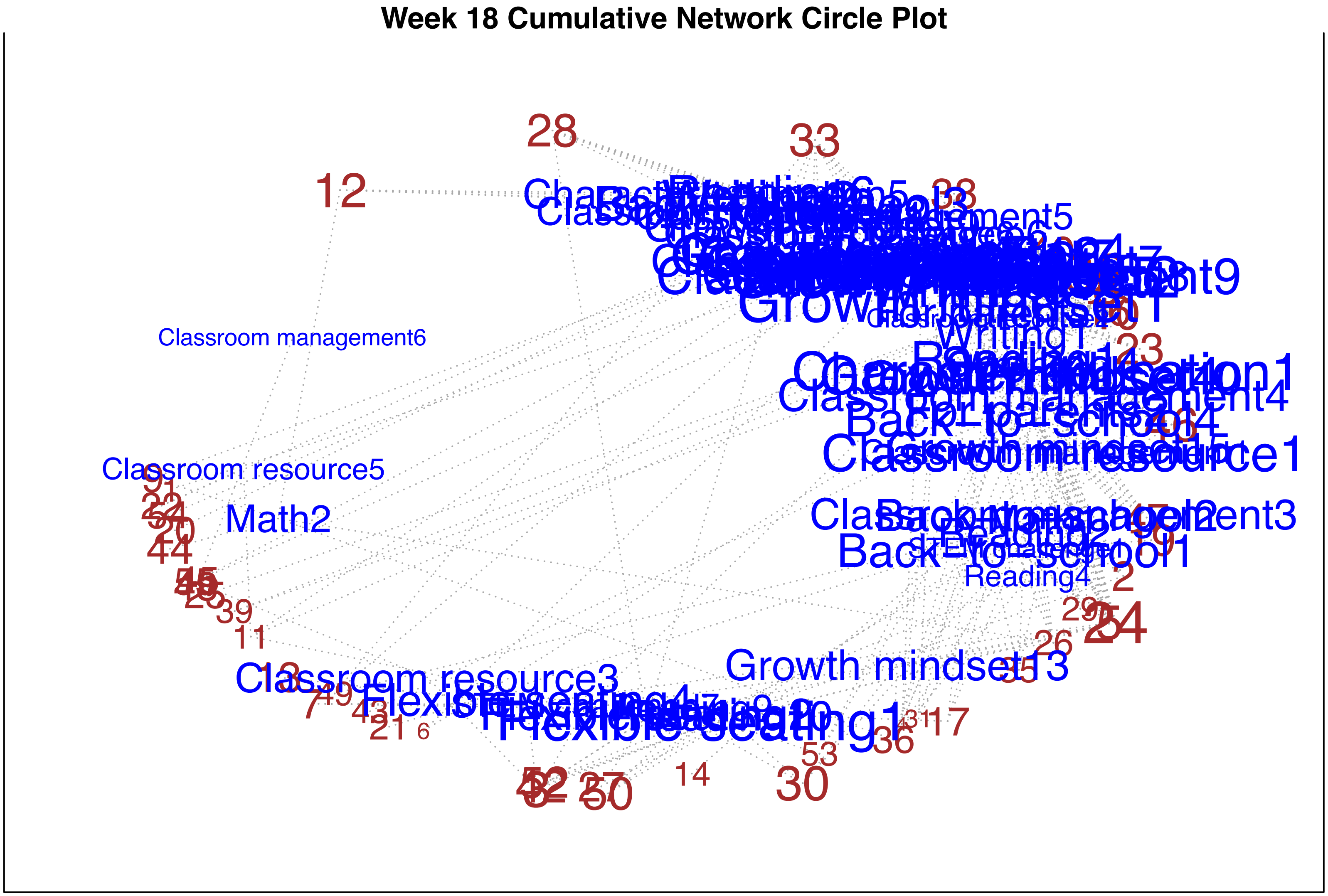


Figure C19. Week 19 Cumulative Network Circle Plot

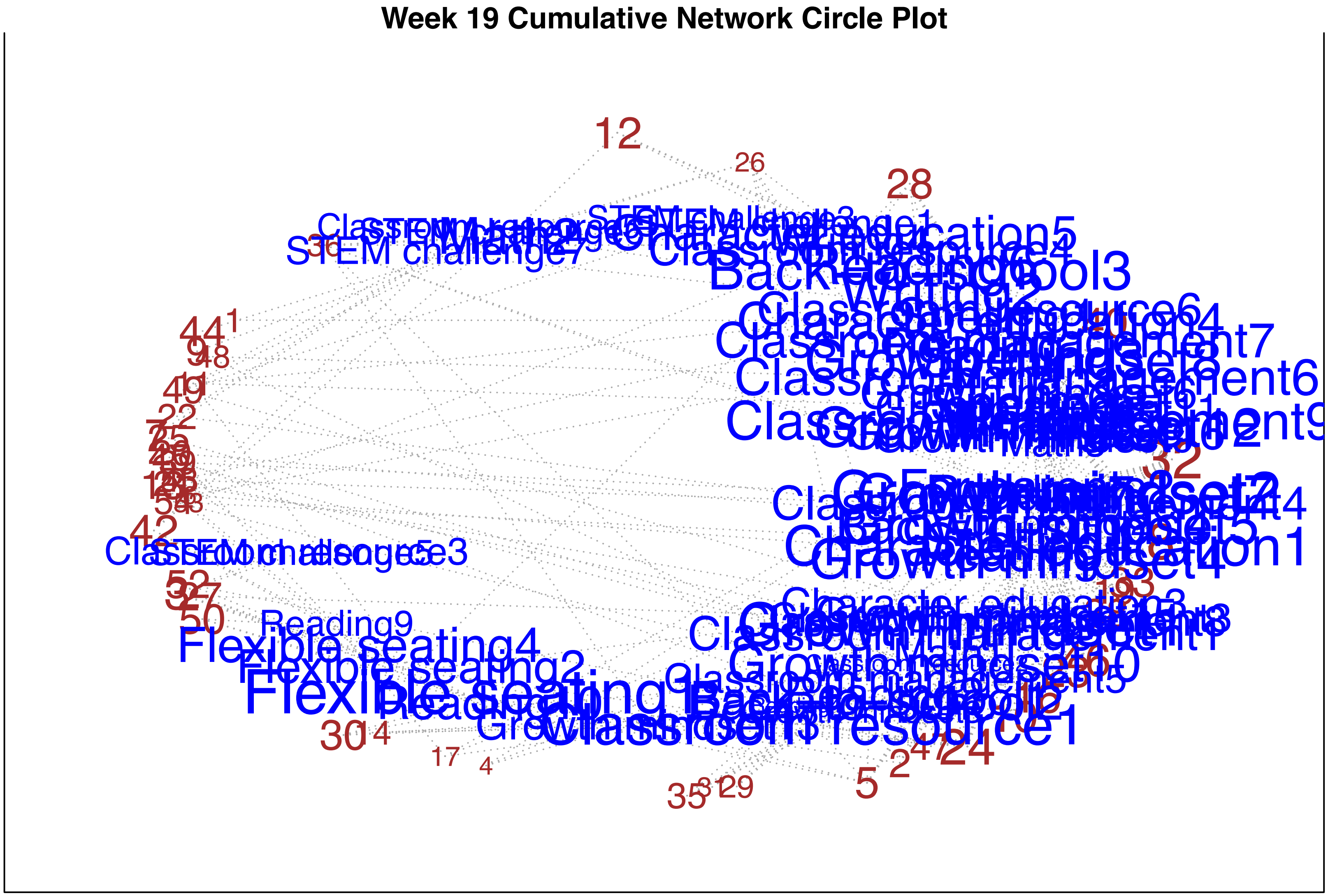


Figure C20. Week 20 Cumulative Network Circle Plot

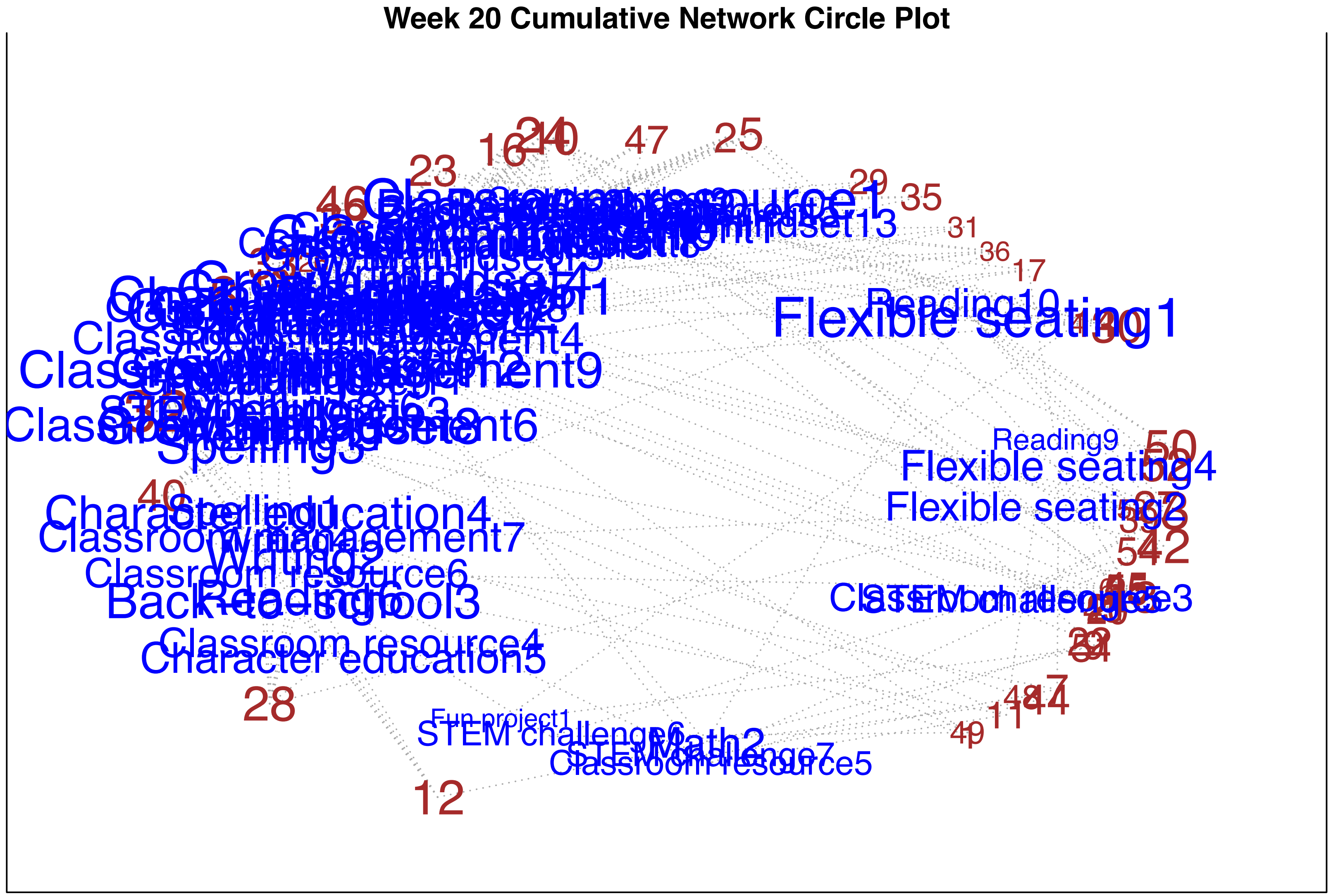


Figure C21. Week 21 Cumulative Network Circle Plot

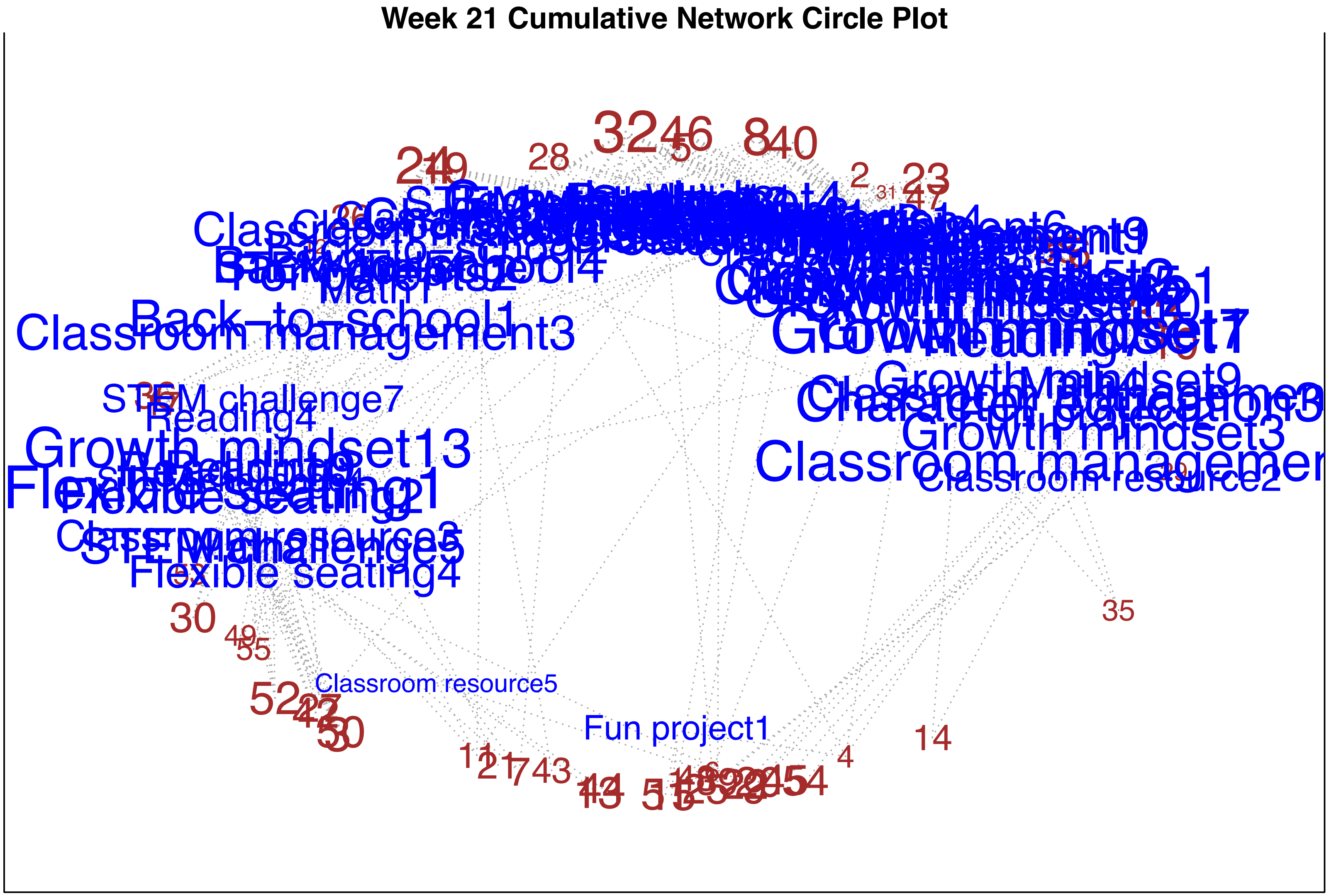


Figure C22. Week 22 Cumulative Network Circle Plot

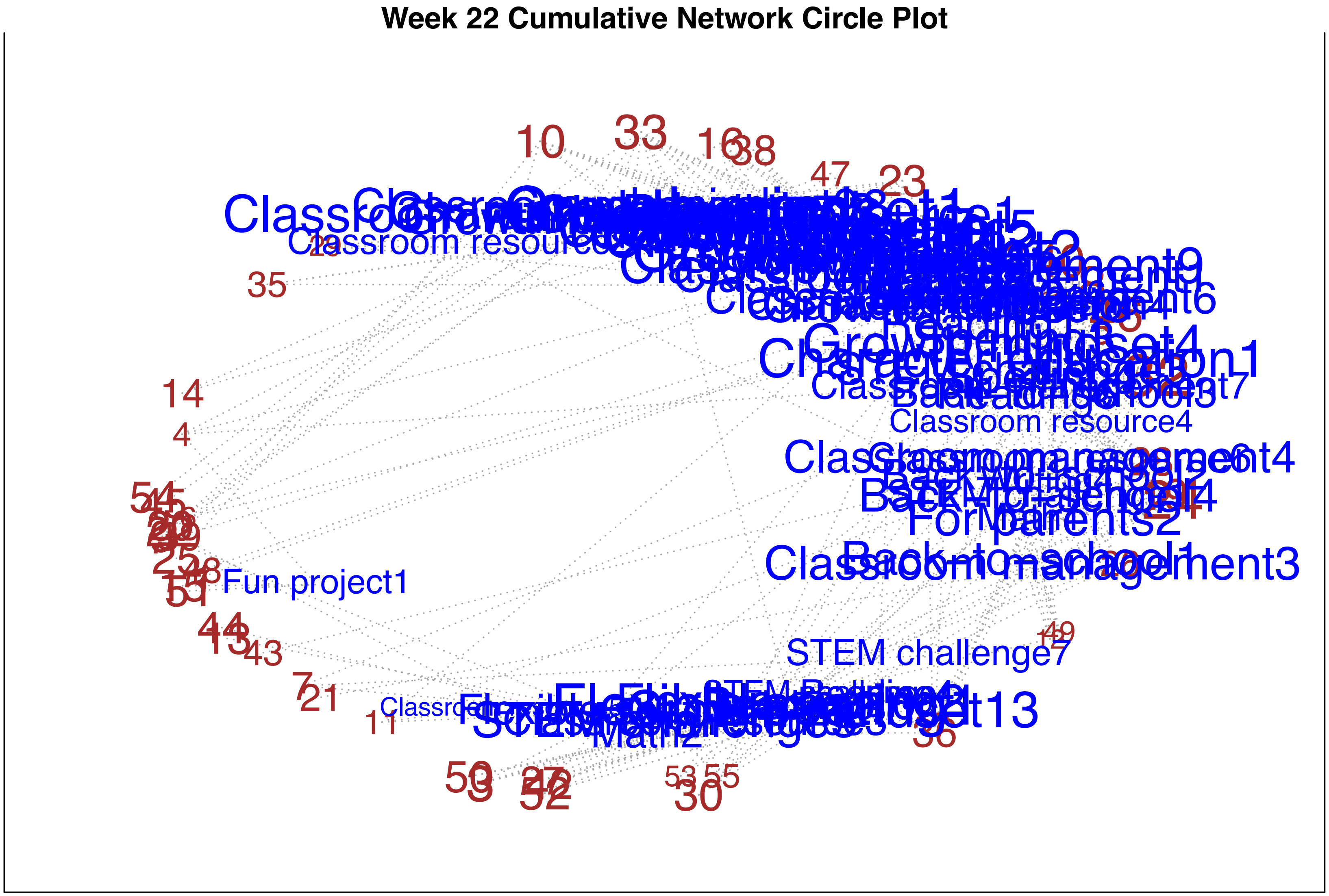


Figure C23. Week 23 Cumulative Network Circle Plot

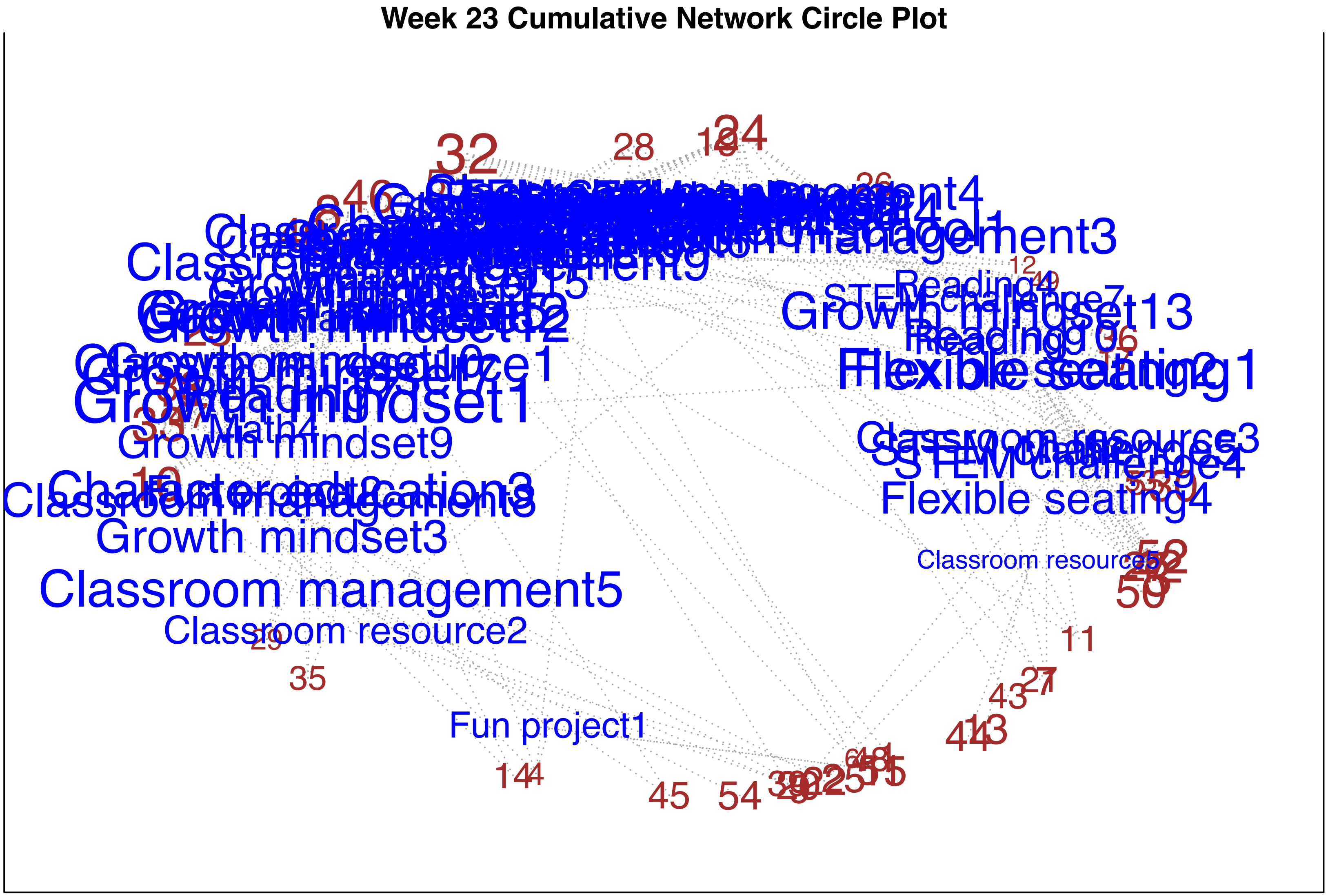


Figure C24. Week 24 Cumulative Network Circle Plot

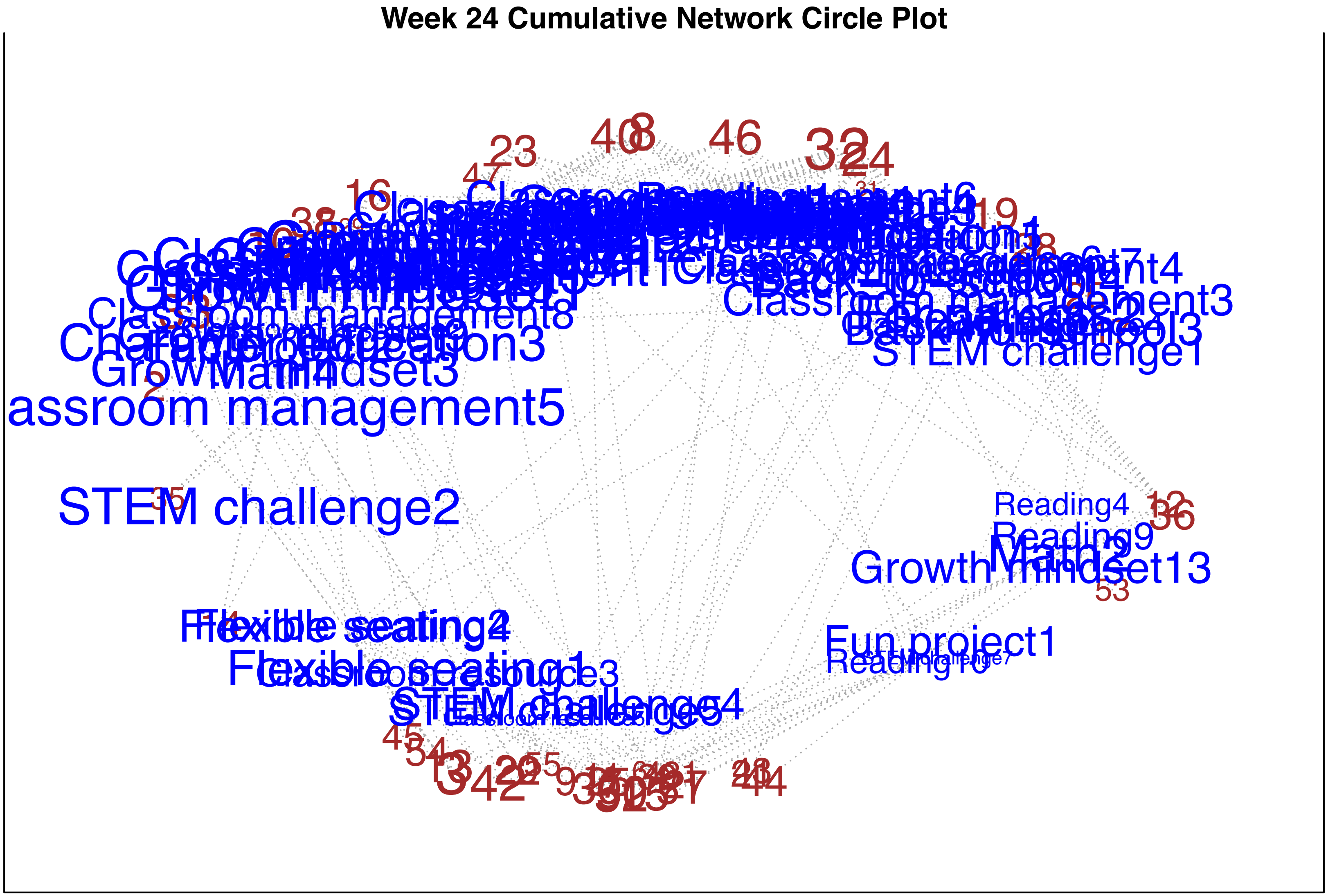


Figure C25. Week 25 Cumulative Network Circle Plot

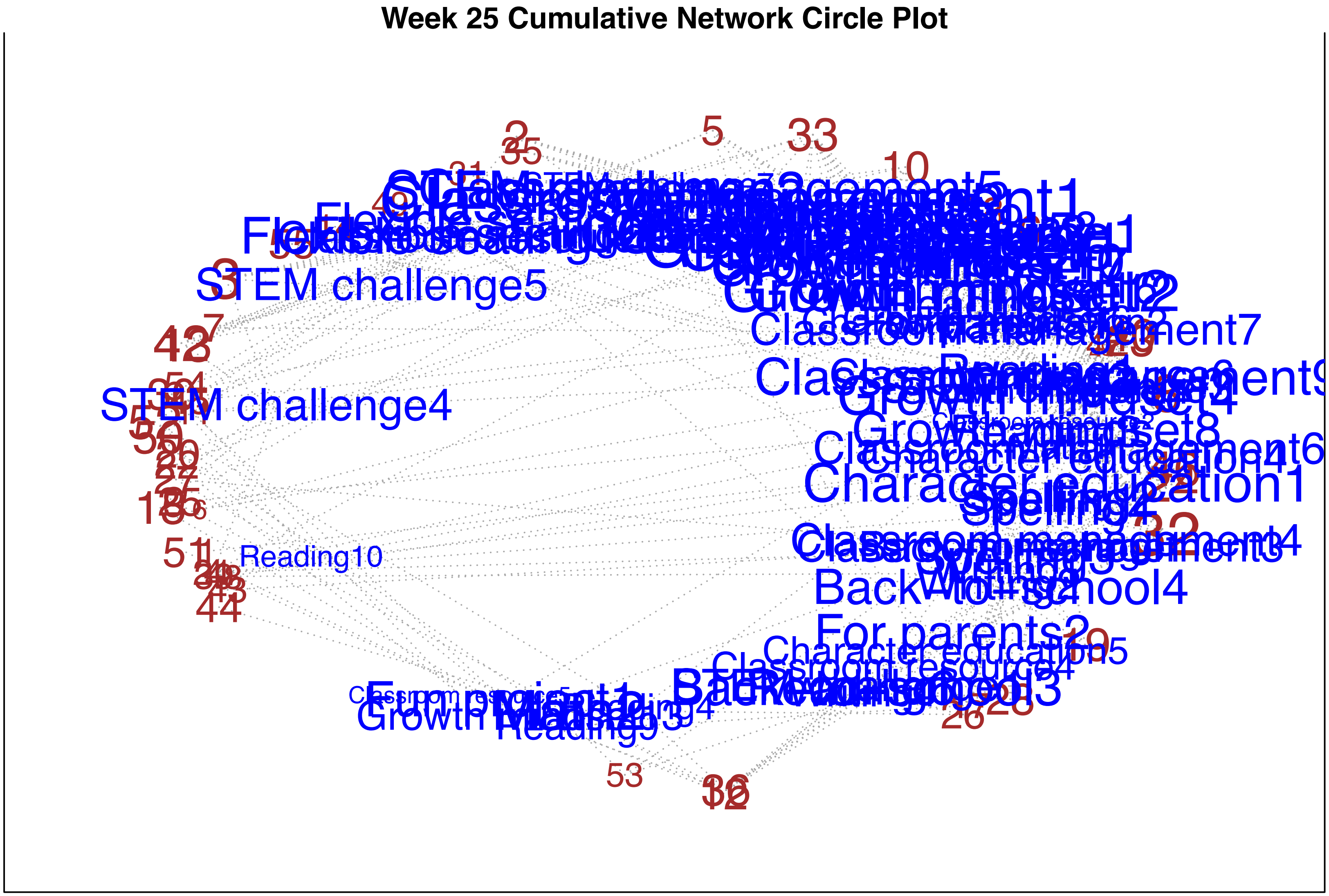


Figure C26. Week 26 Cumulative Network Circle Plot

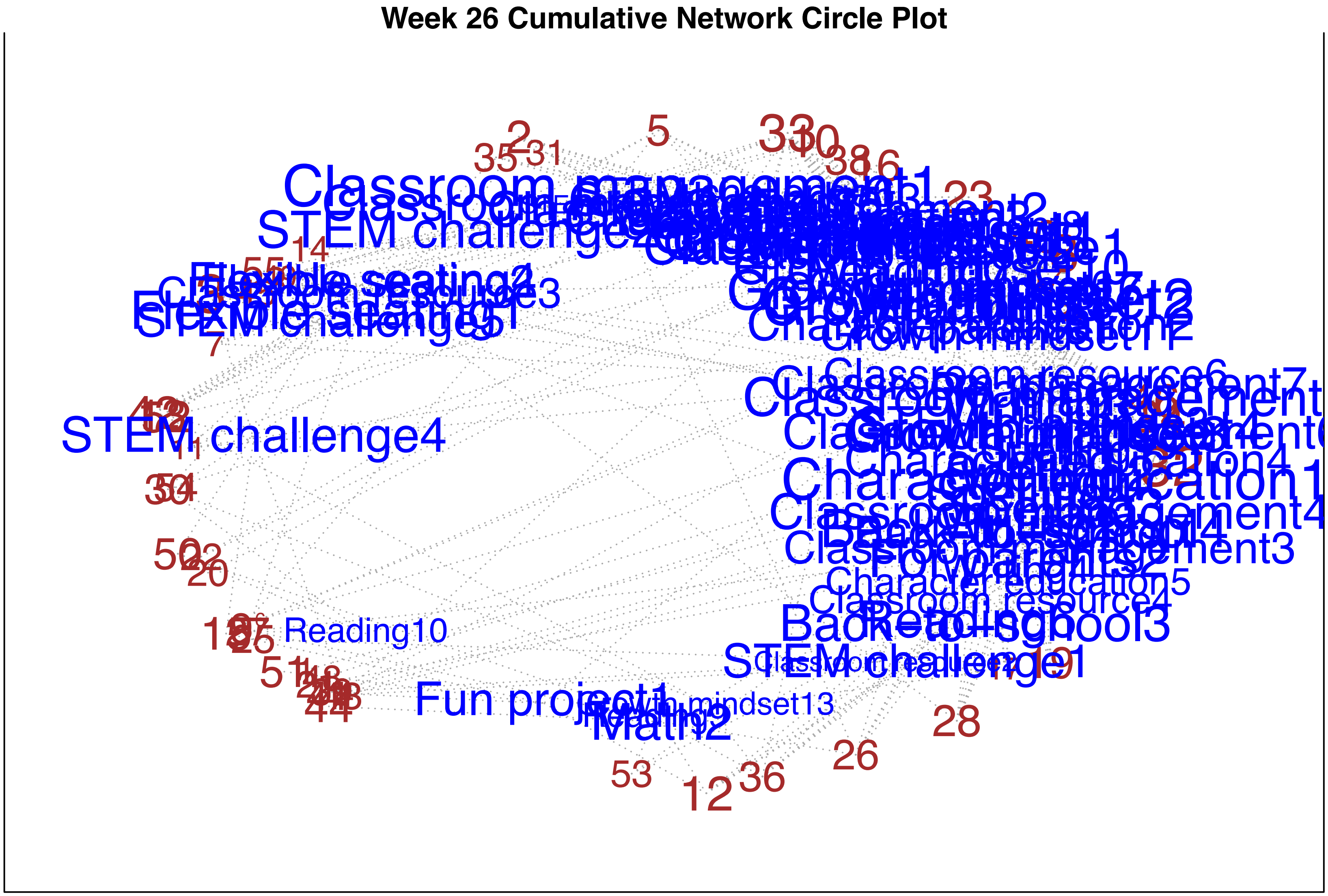


Figure C27. Week 27 Cumulative Network Circle Plot

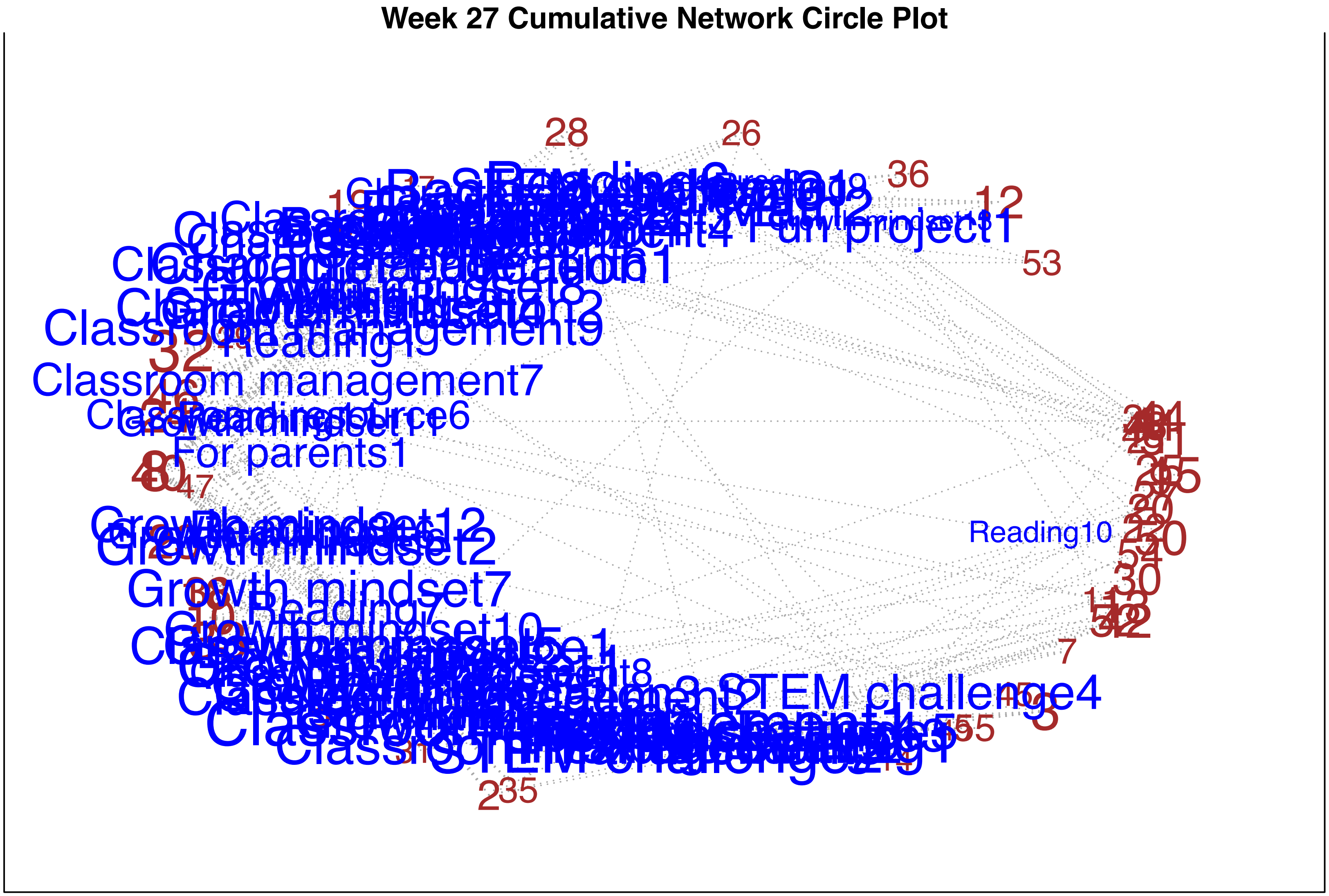


Figure C28. Week 28 Cumulative Network Circle Plot

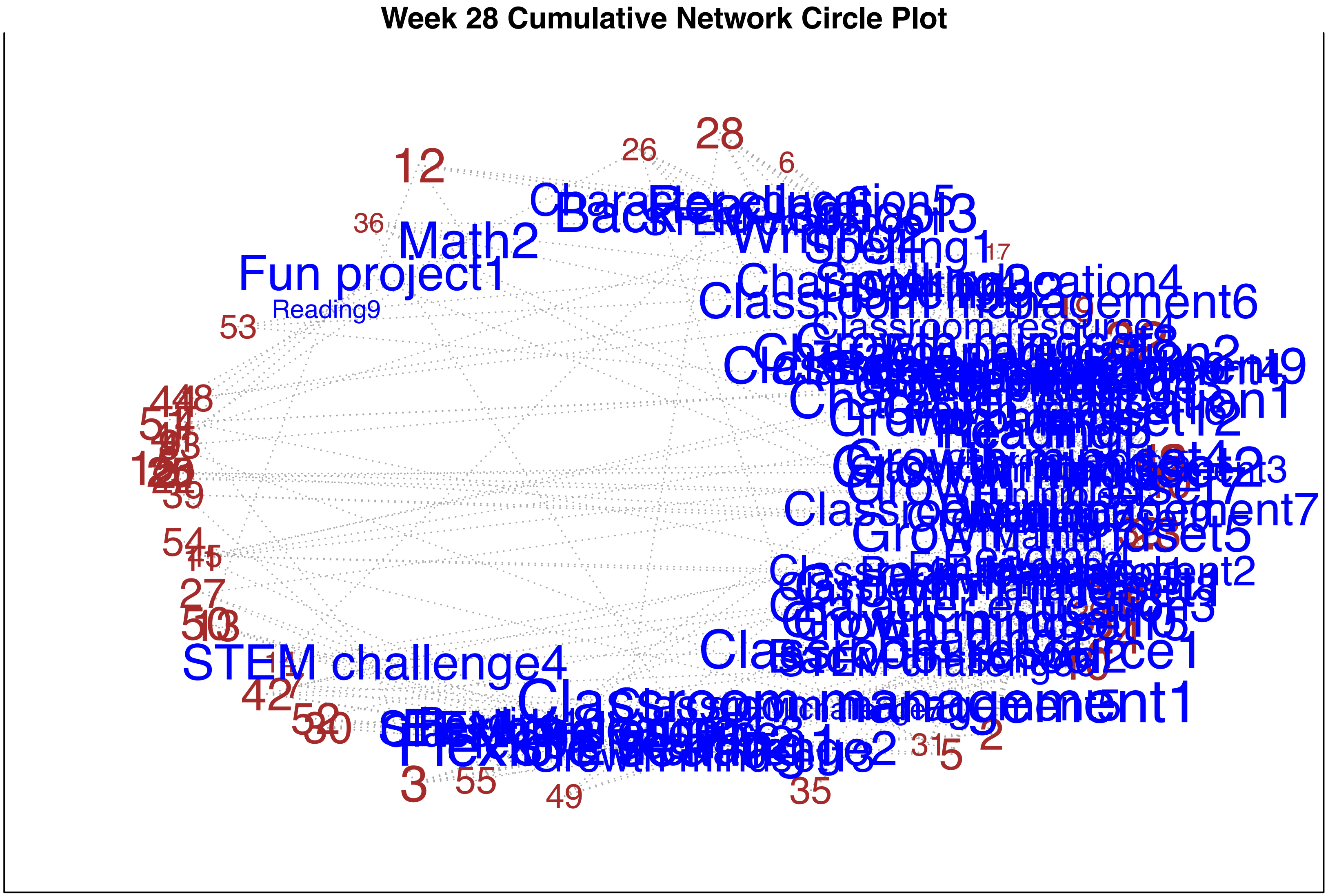


Figure C29. Week 29 Cumulative Network Circle Plot

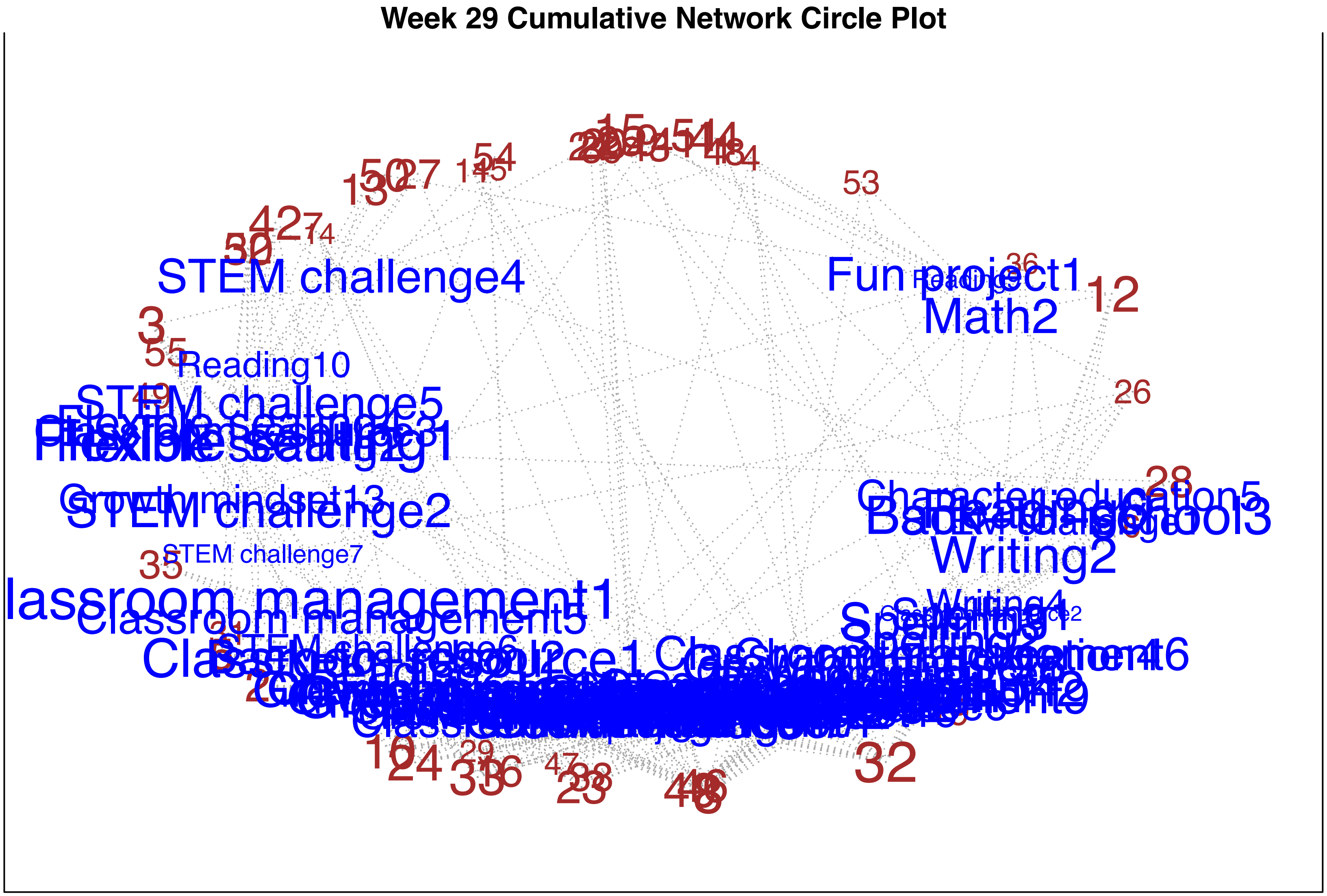


Figure C30. Week 30 Cumulative Network Circle Plot

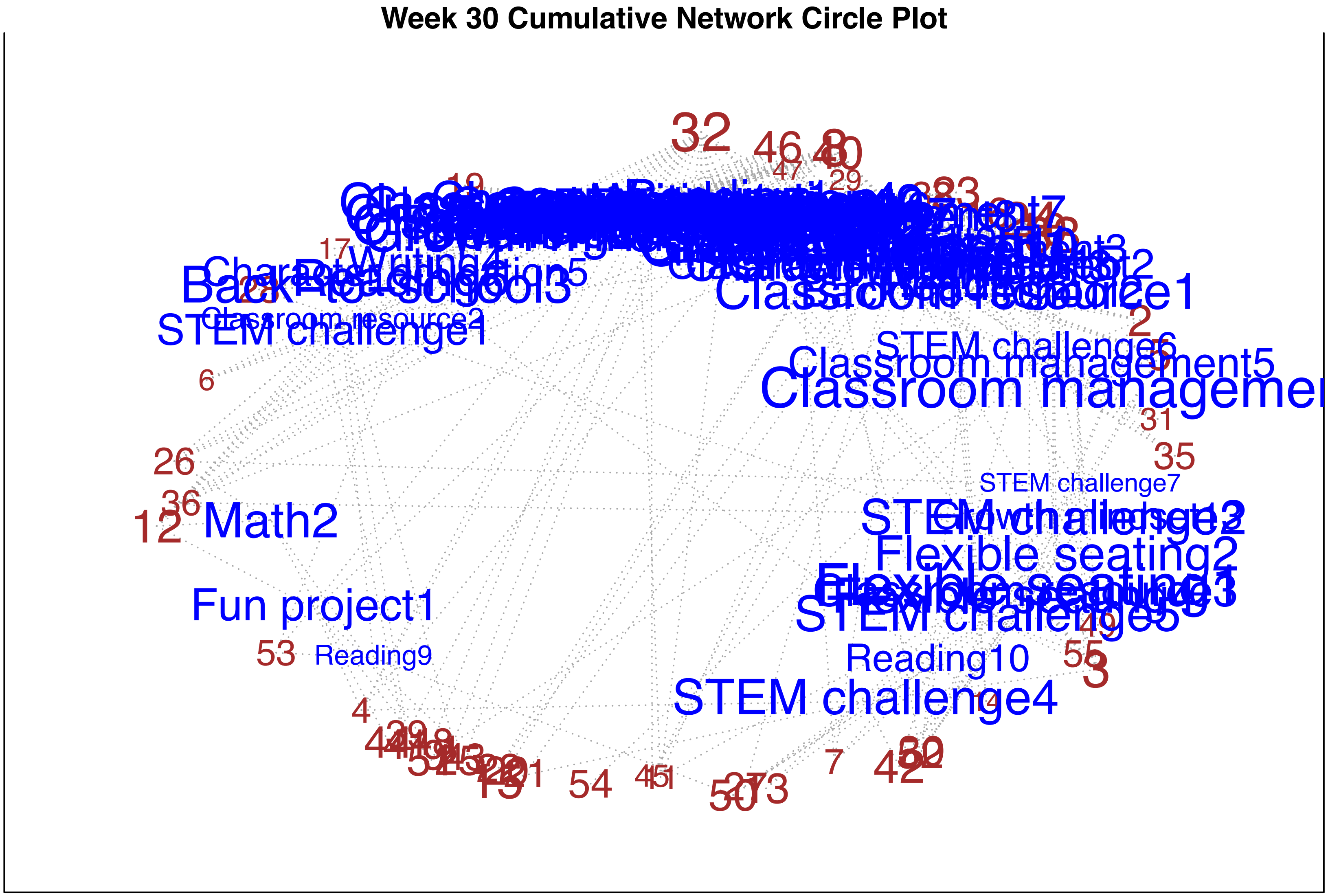


Figure C31. Week 31 Cumulative Network Circle Plot

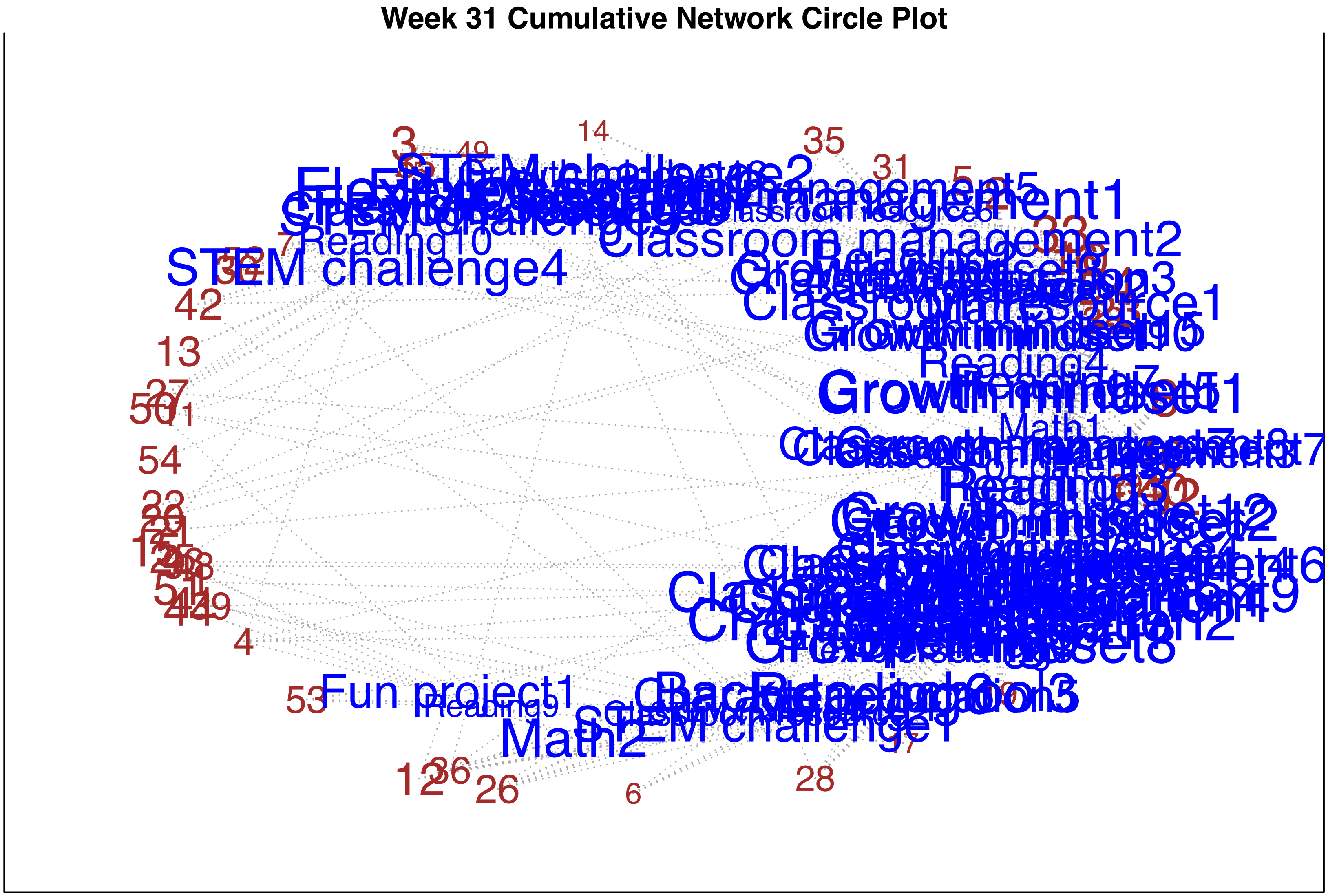


Figure C32. Week 32 Cumulative Network Circle Plot

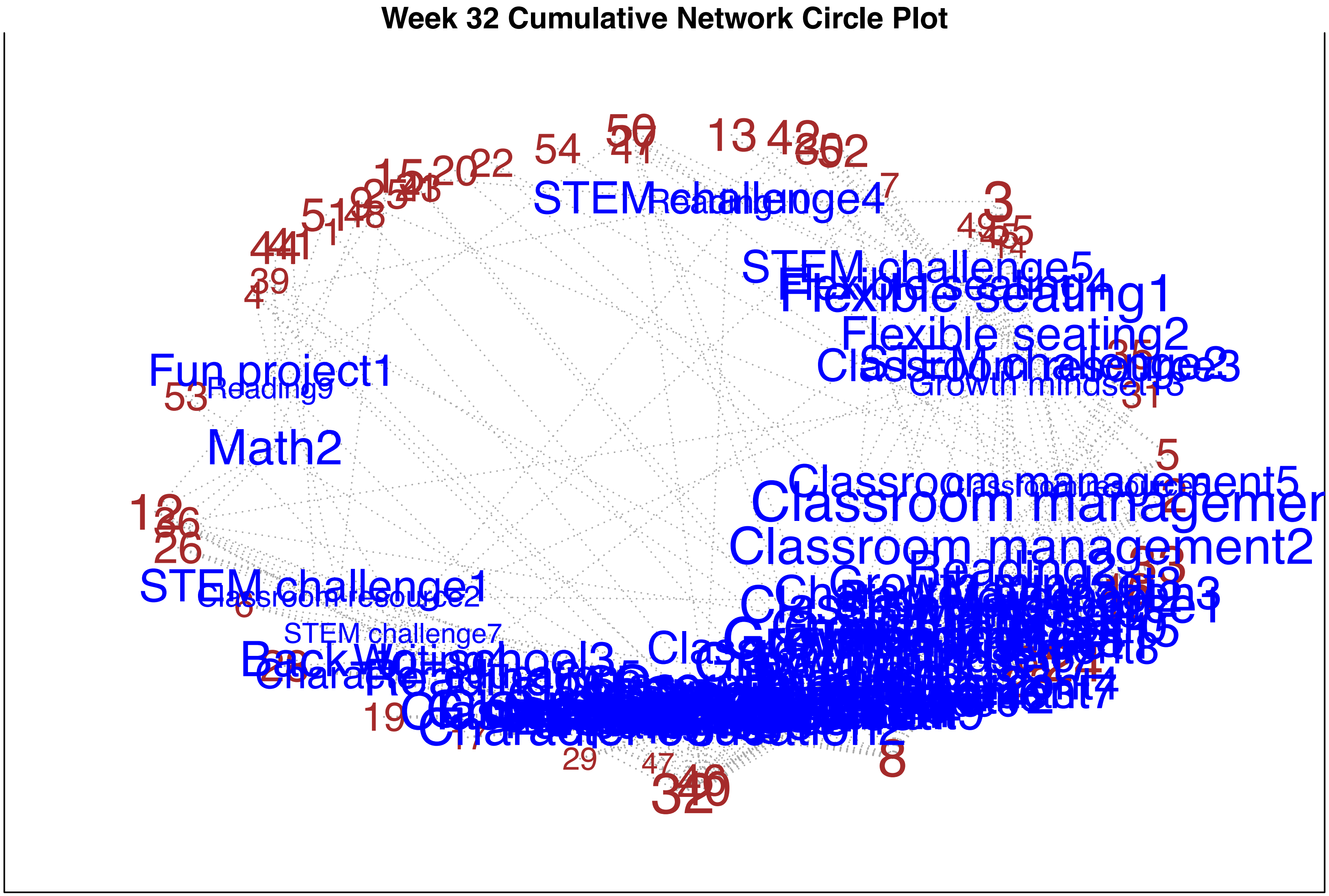


Figure C33. Week 33 Cumulative Network Circle Plot

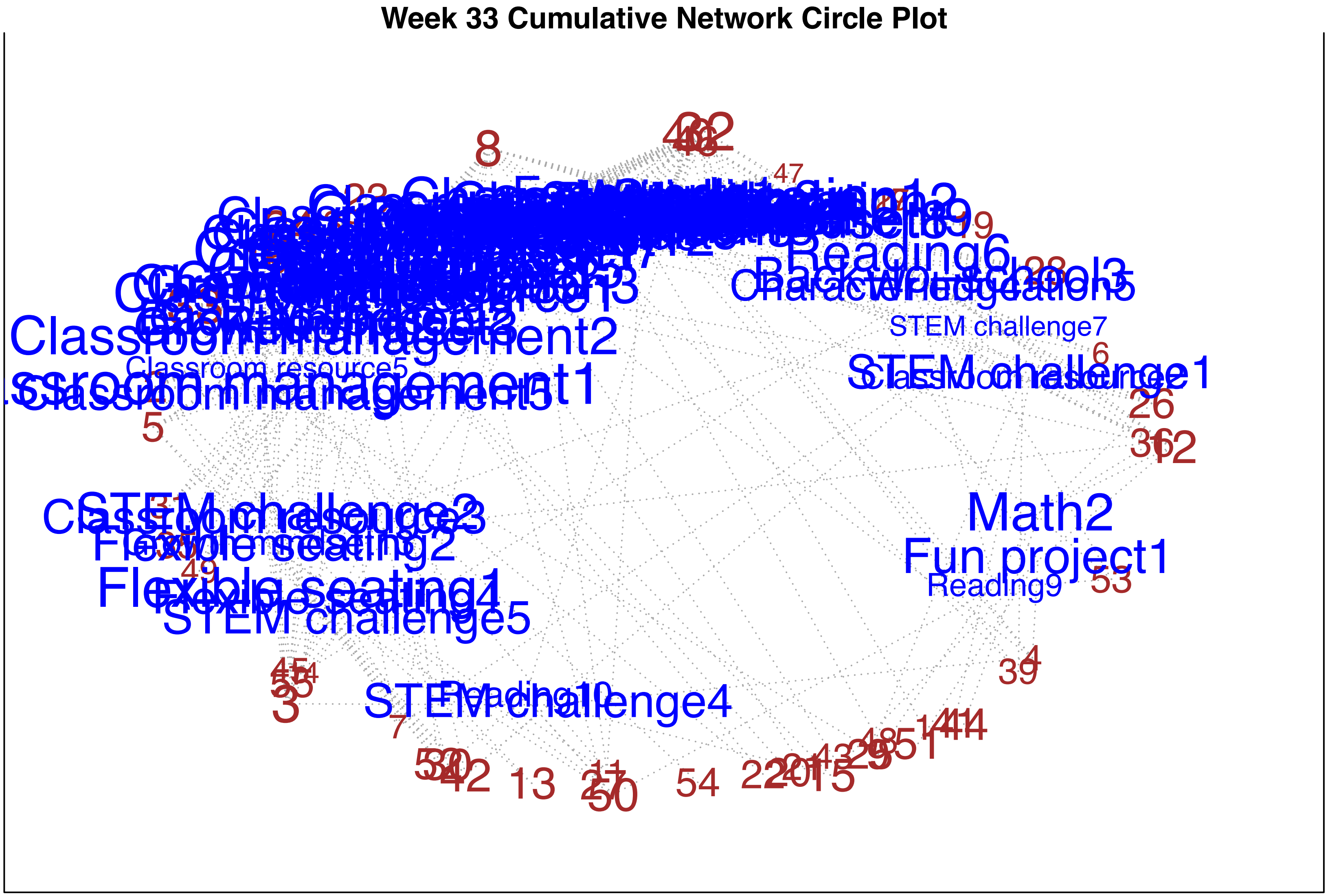


Figure C34. Week 34 Cumulative Network Circle Plot

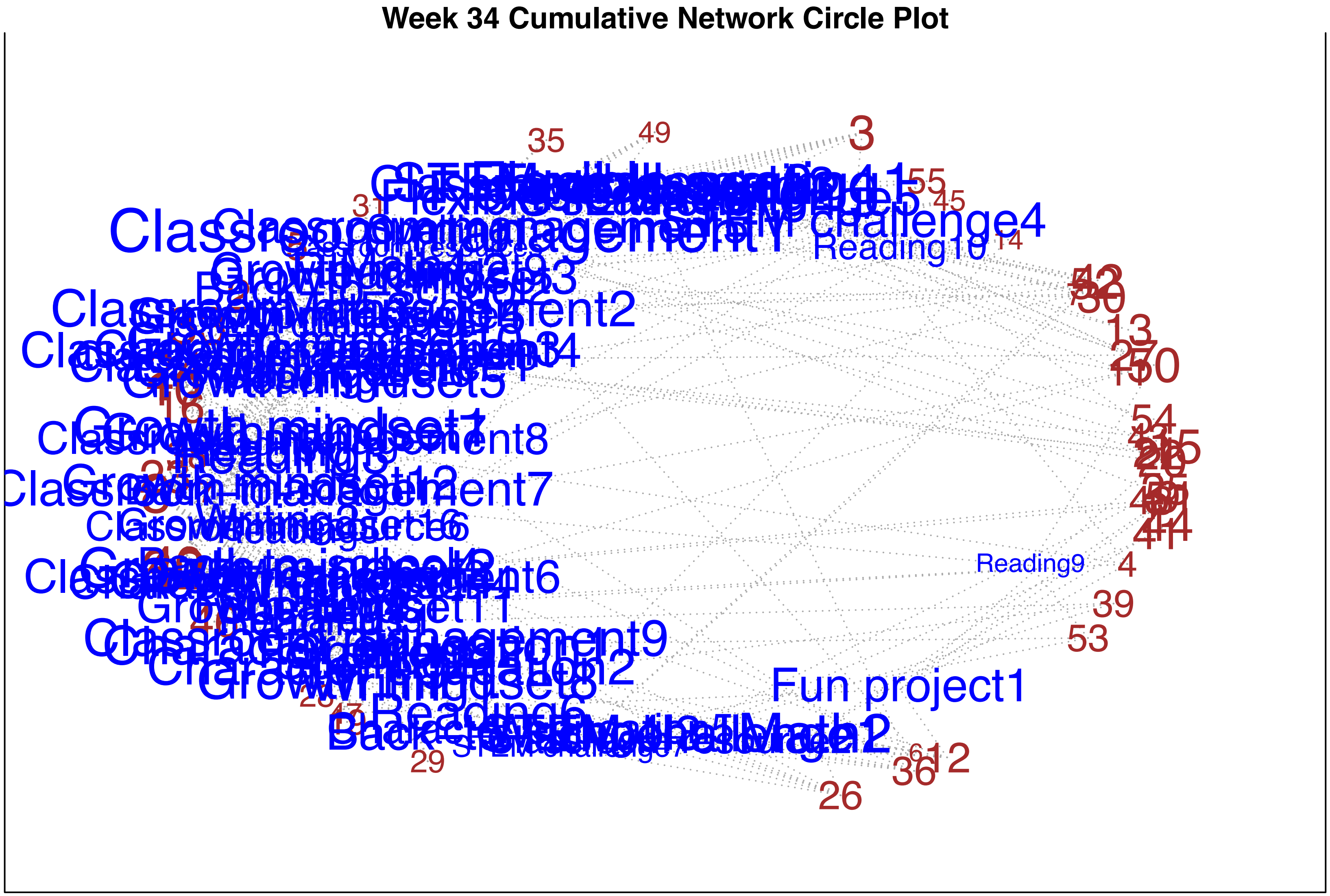


Figure C35. Week 35 Cumulative Network Circle Plot

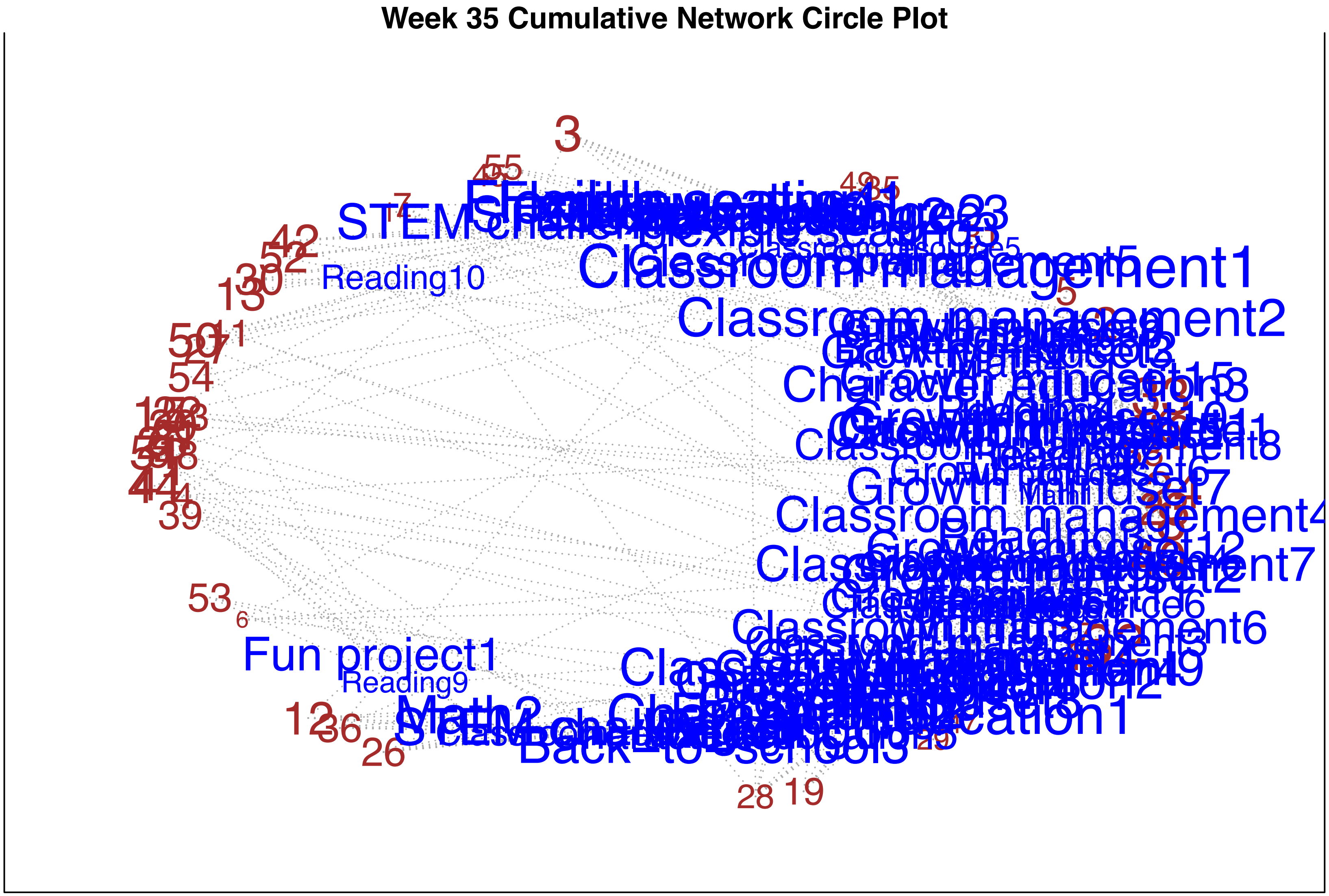


Figure C36. Week 36 Cumulative Network Circle Plot

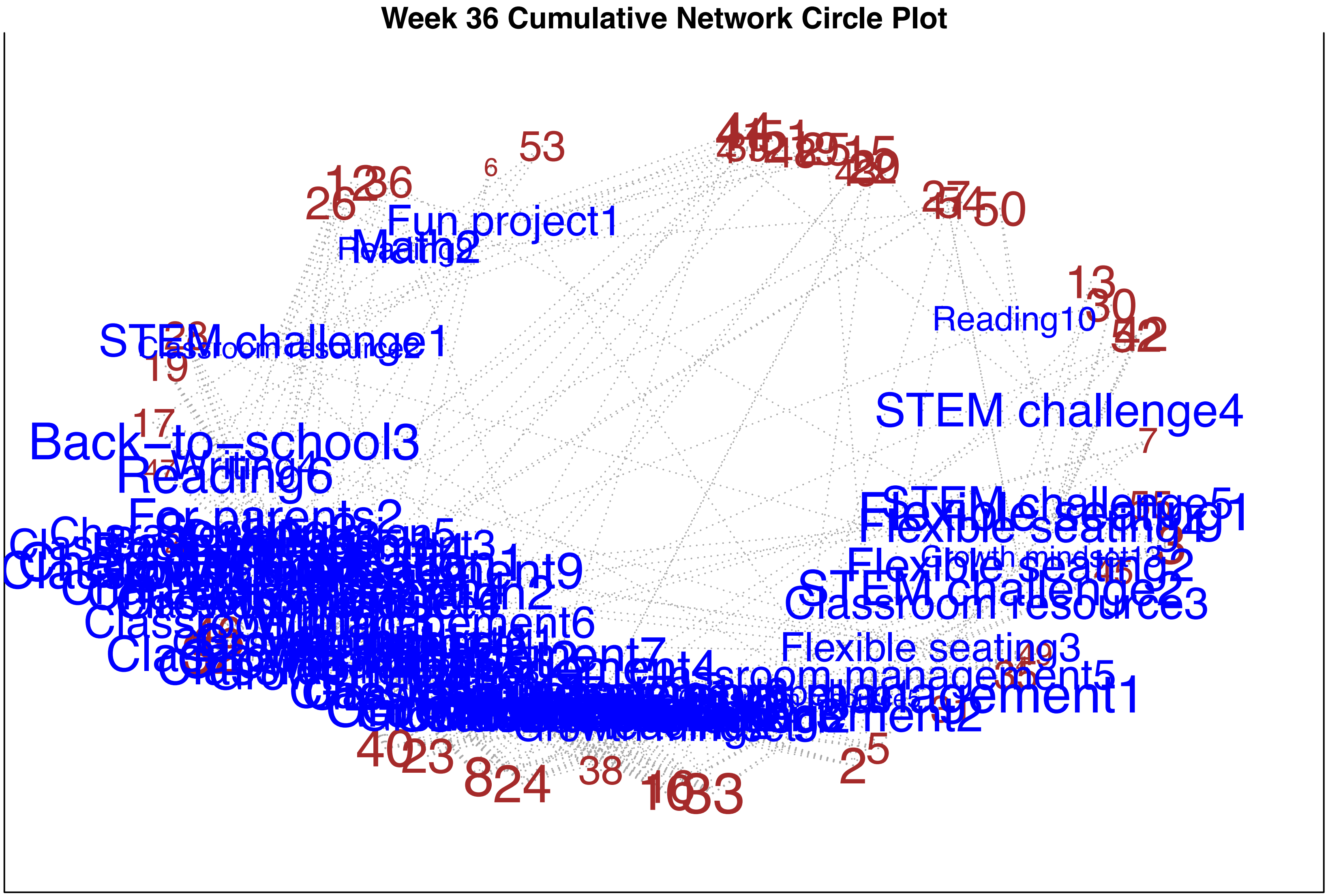


Figure C37. Week 37 Cumulative Network Circle Plot

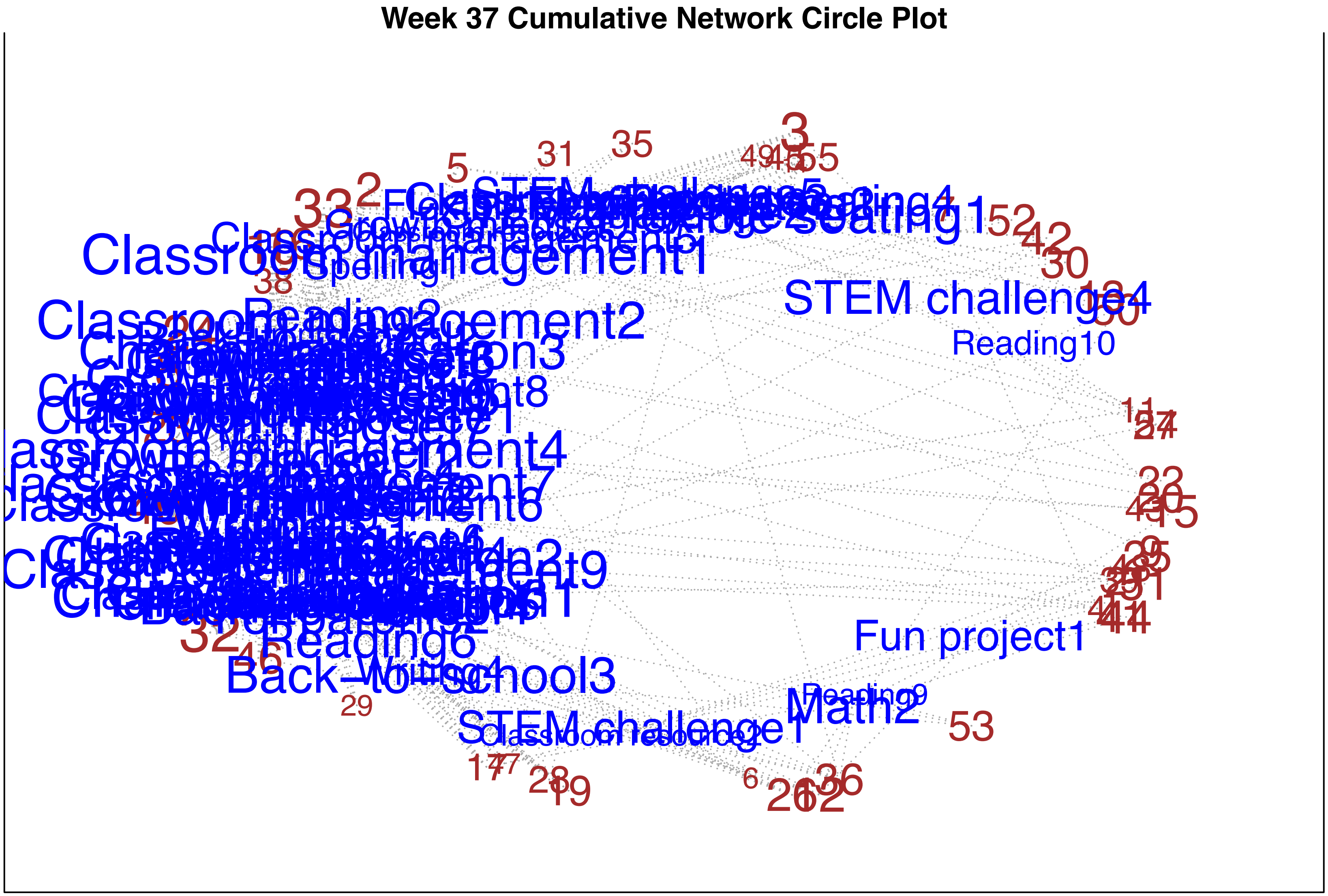


Figure C38. Week 38 Cumulative Network Circle Plot

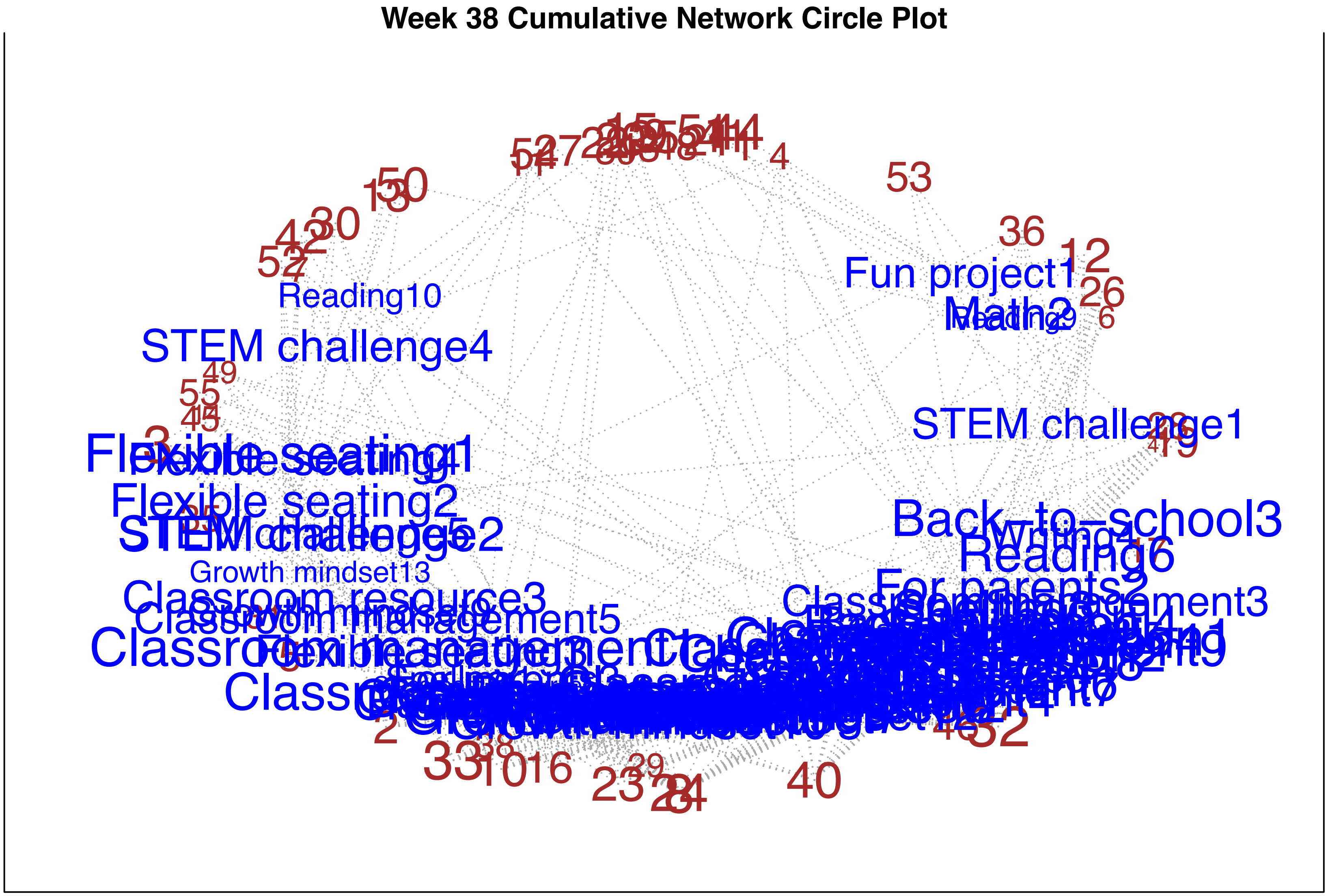


Figure C39. Week 39 Cumulative Network Circle Plot

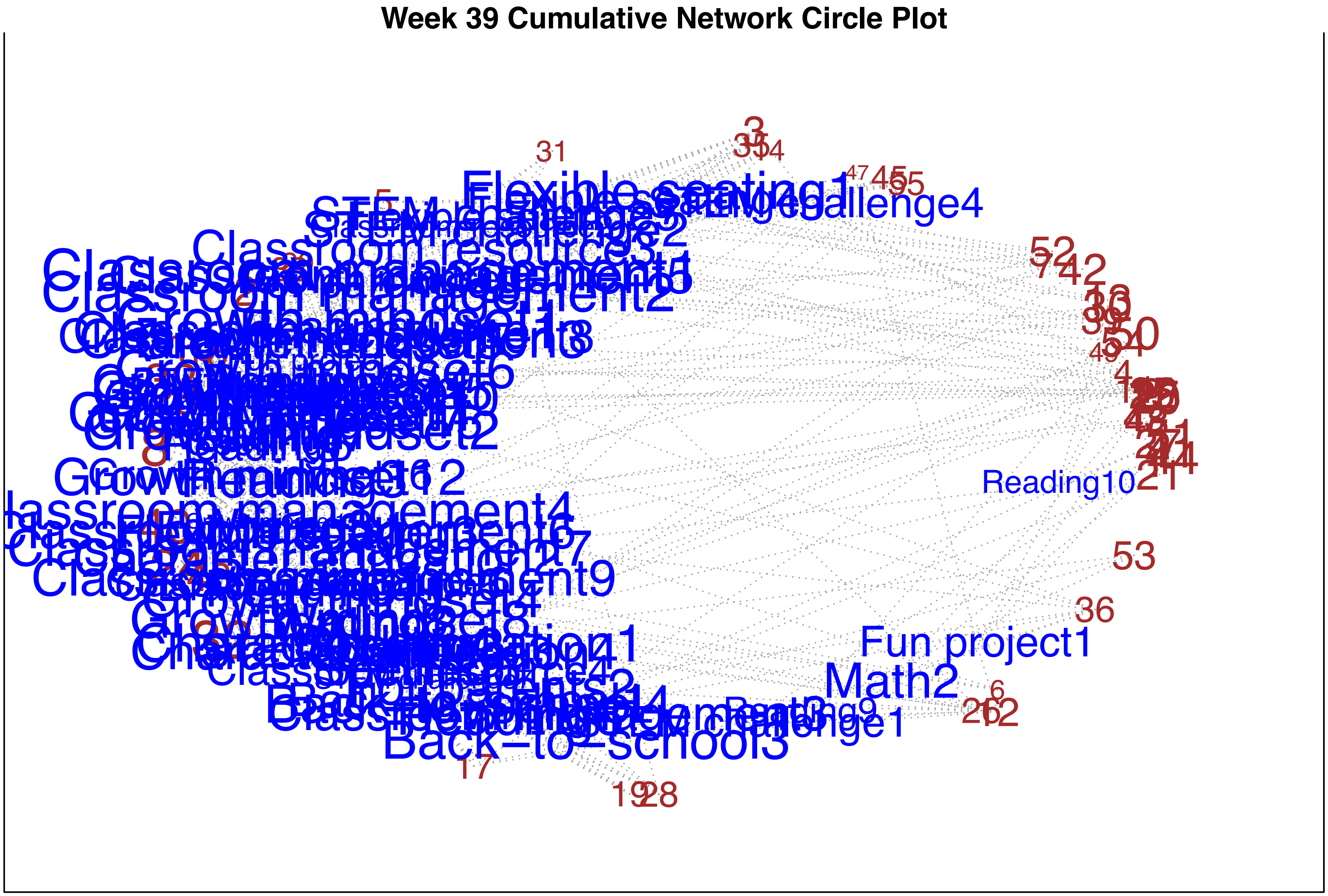


Figure C40. Week 40 Cumulative Network Circle Plot

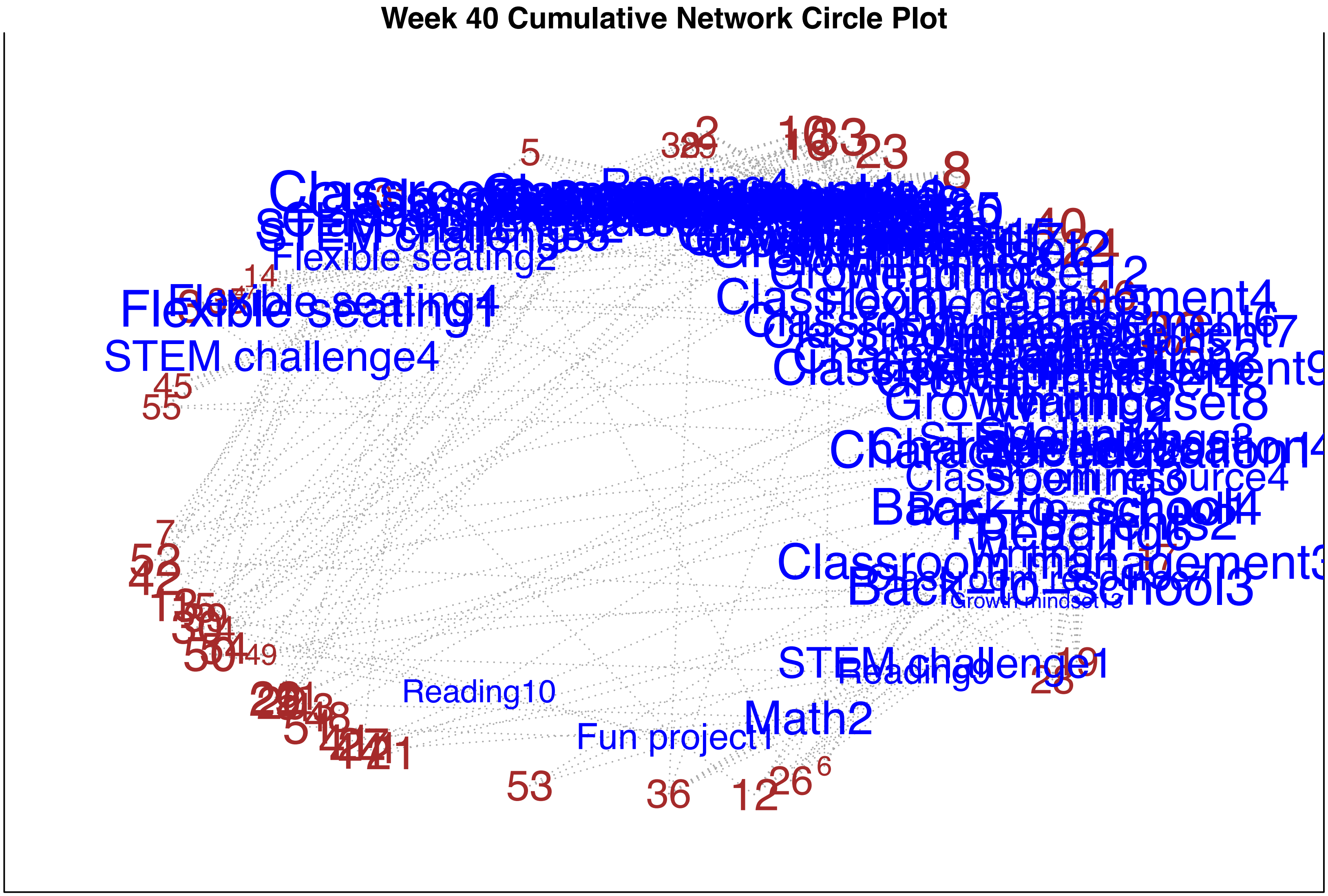


Figure C41. Week 41 Cumulative Network Circle Plot

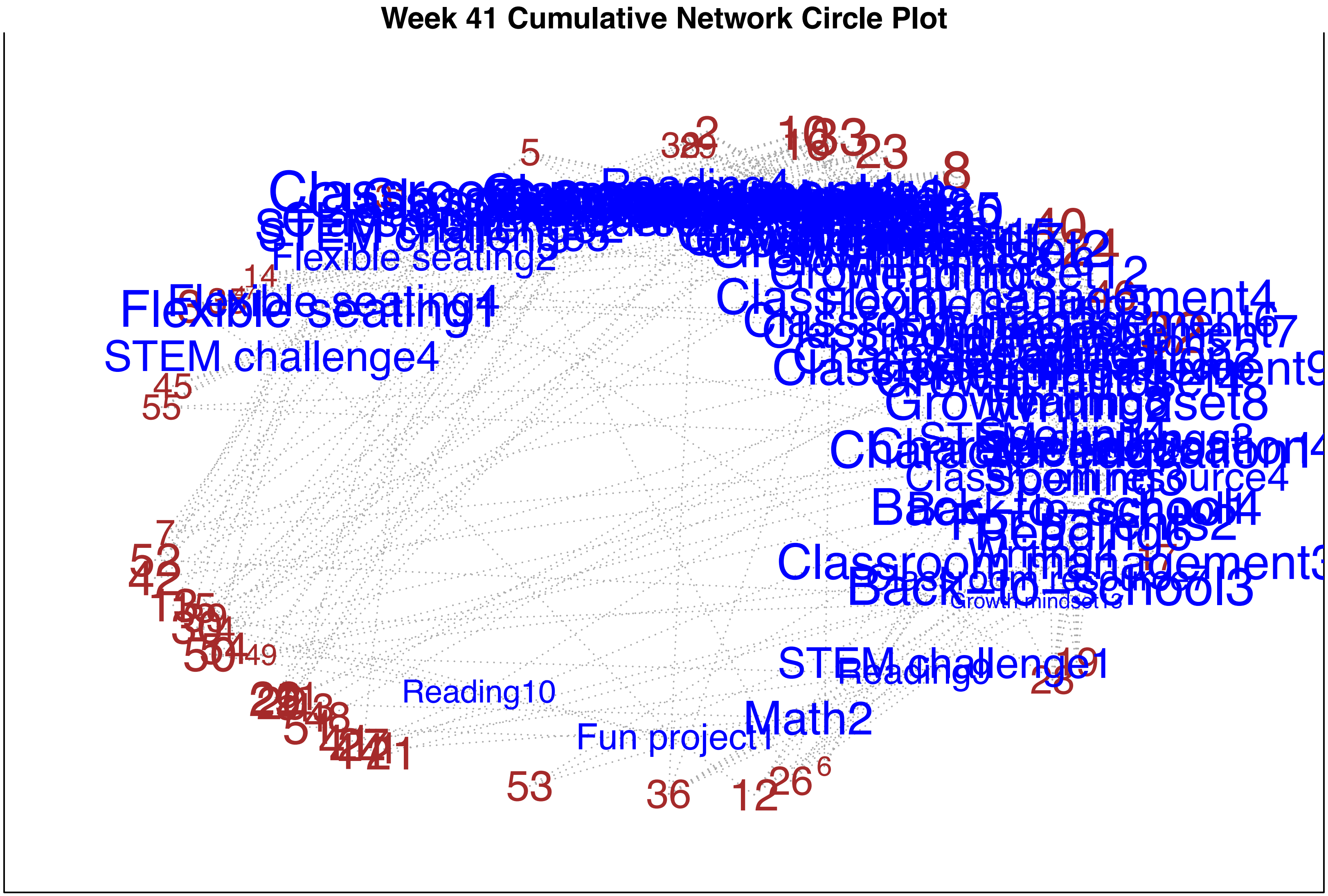


Figure C42. Week 42 Cumulative Network Circle Plot

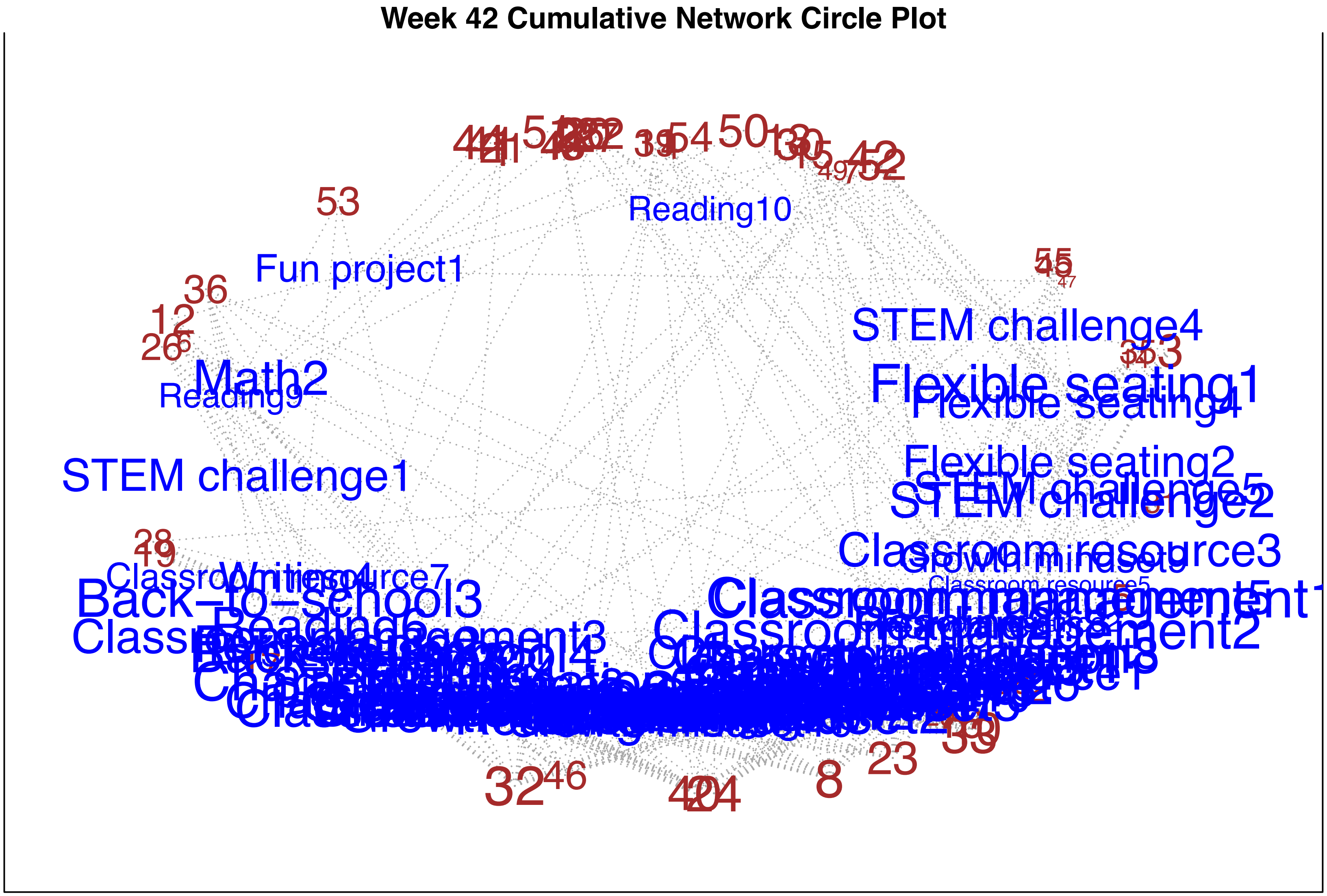


Figure C43. Week 43 Cumulative Network Circle Plot

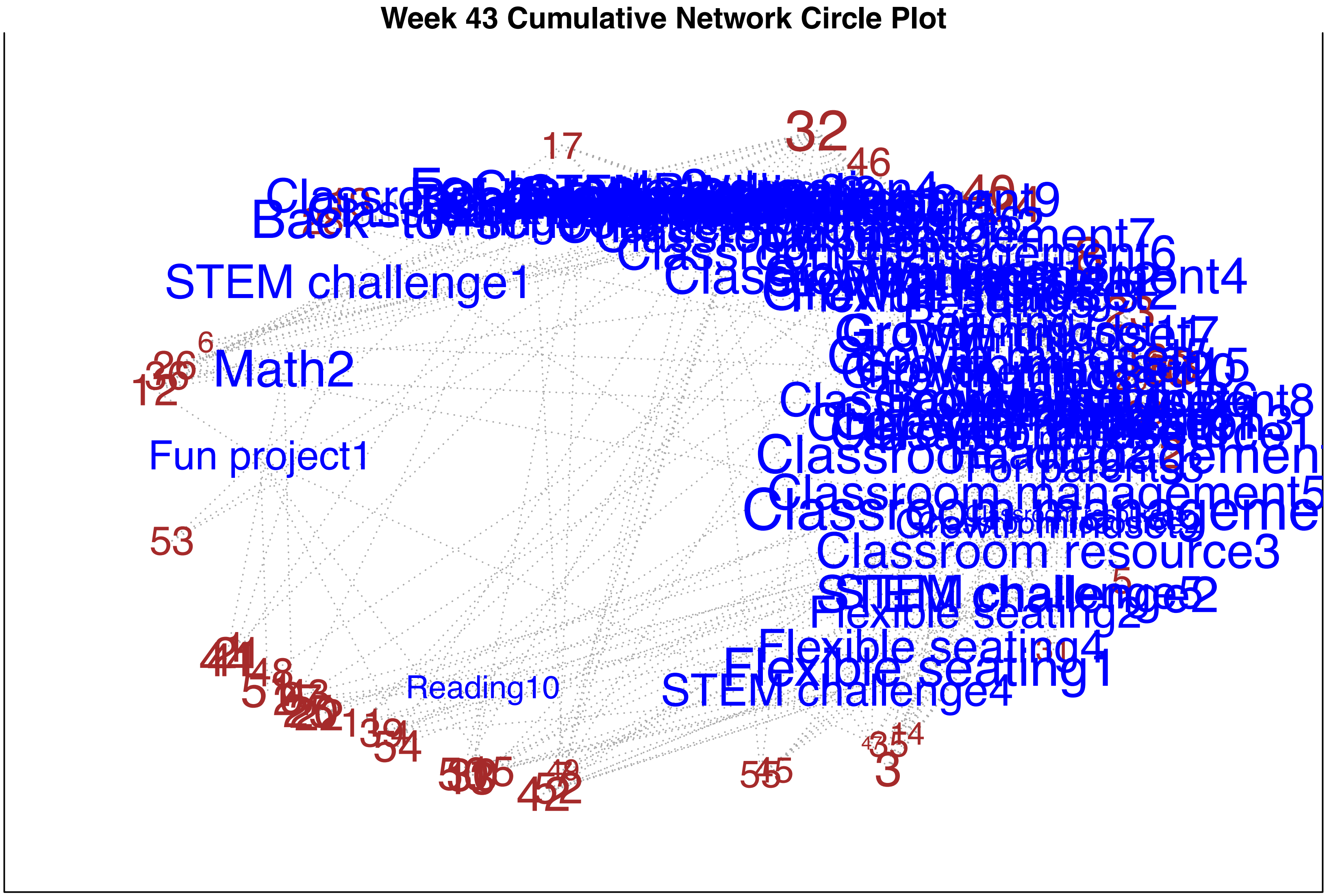


Figure C44. Week 44 Cumulative Network Circle Plot

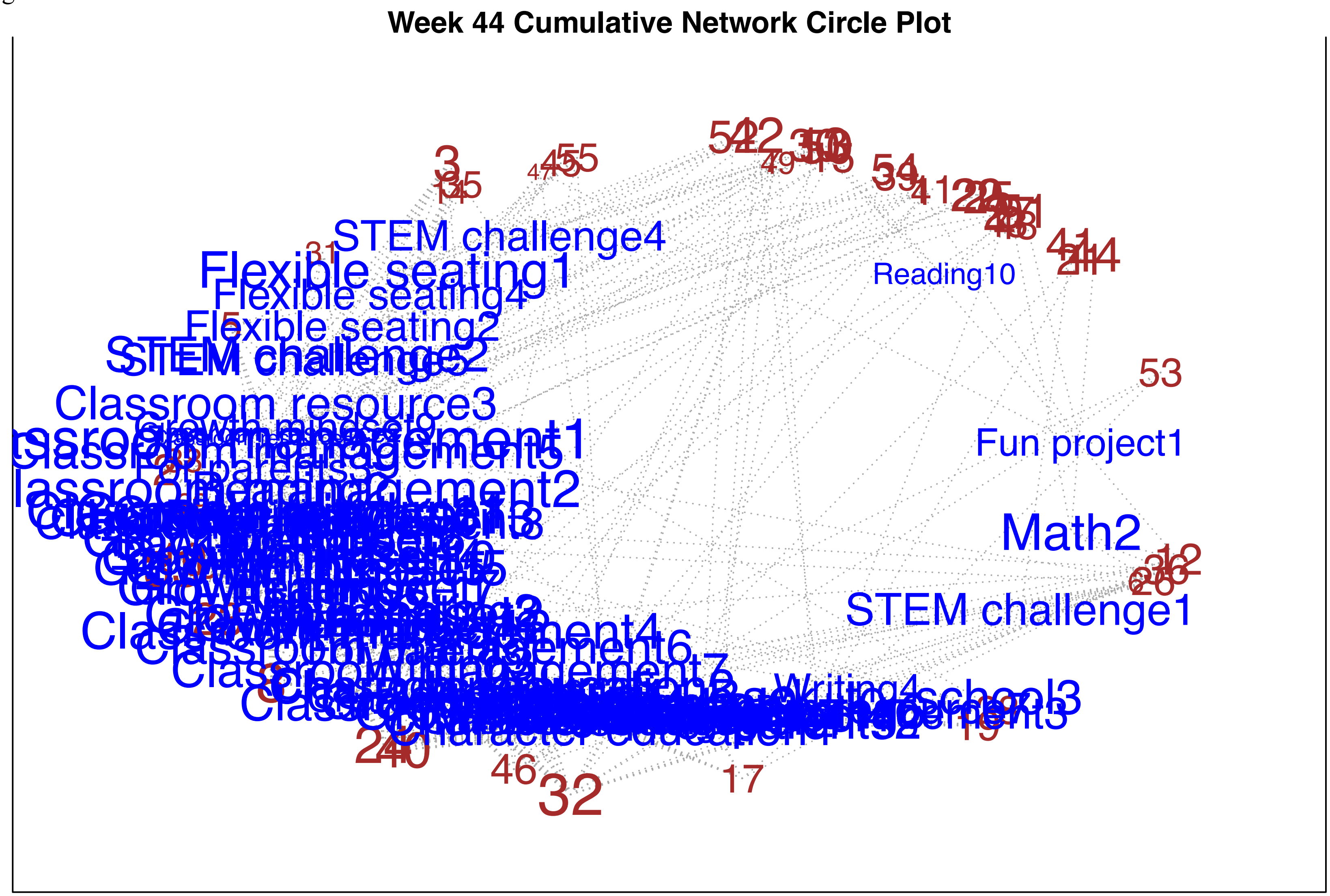


Figure C45. Week 45 Cumulative Network Circle Plot

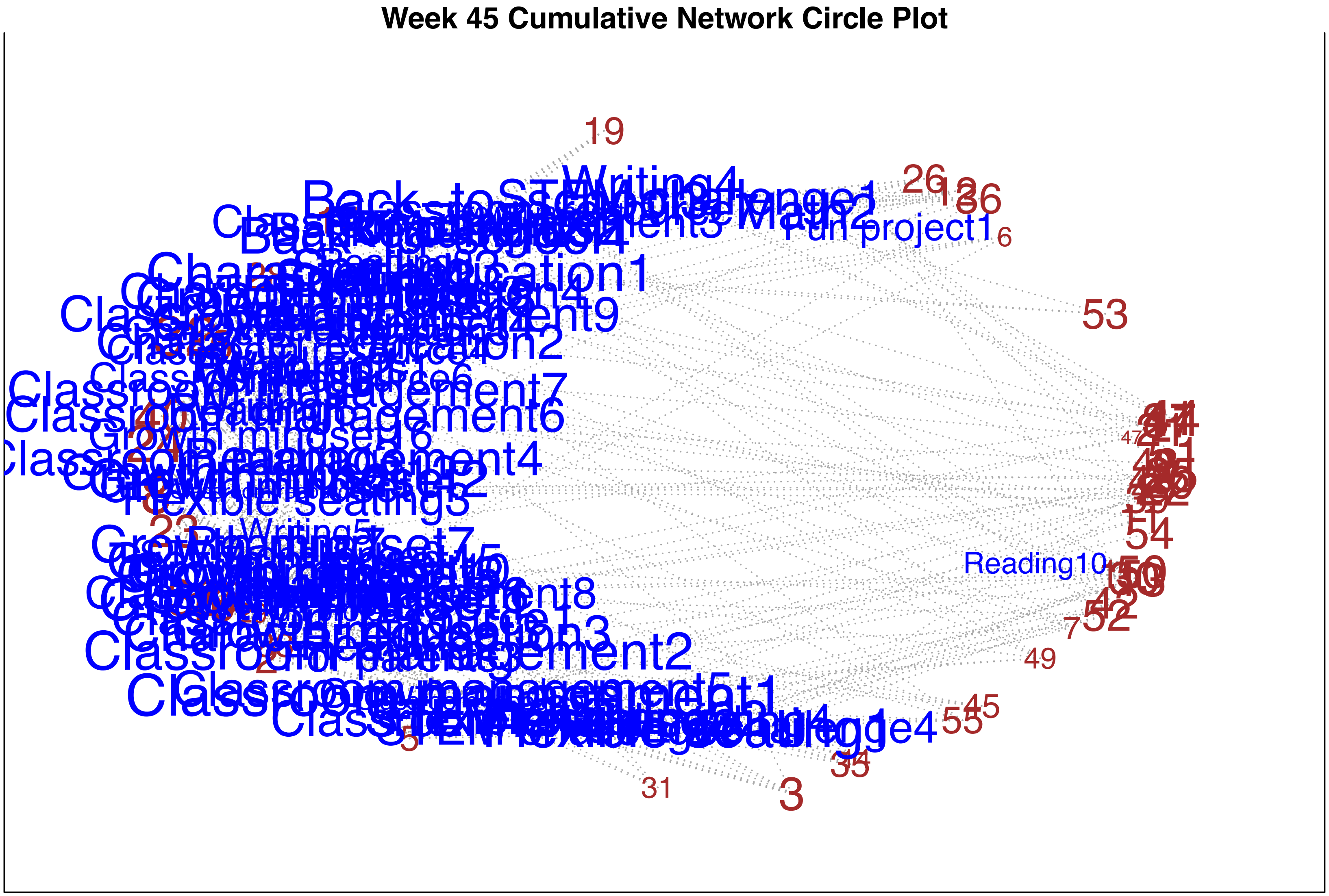


Figure C46. Week 46 Cumulative Network Circle Plot

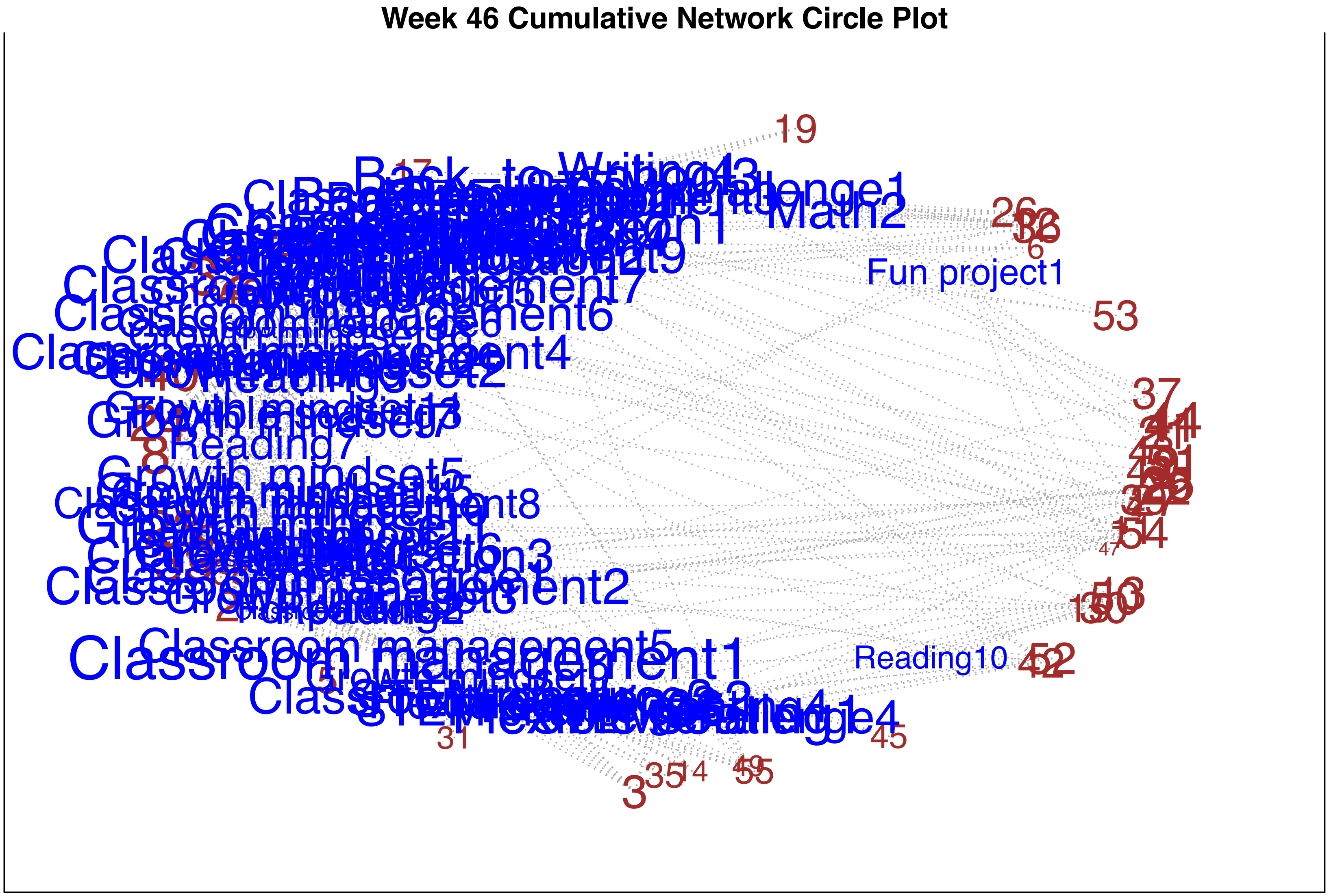
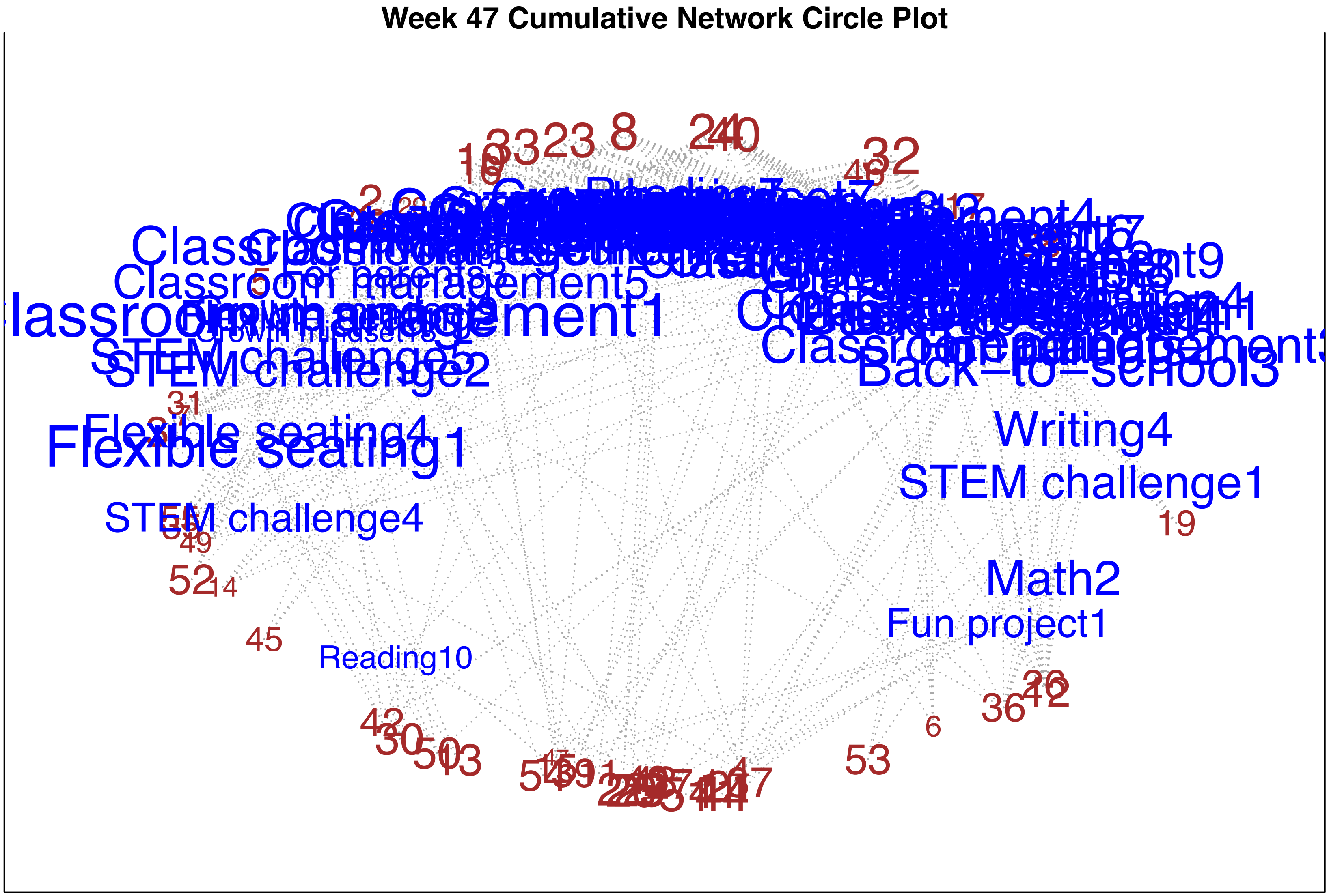


Figure C47. Week 47 Cumulative Network Circle Plot



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