Using Network Science to Measure Centrality and Standardness in Event Knowledge

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Abstract

An important issue in event cognition concerns how activities come to mind when people think about events (*eat at a restaurant*). Linear theories suggest that people think of activities in a temporally linear order, whereas hierarchical theories suggest that activities come to mind based on their centrality (i.e., importance). The current study used five network science centrality measures (CheiRank, PageRank, 2D Rank, Betweenness, and Closeness) derived from 80 temporally structured event networks to predict participants' centrality and standardness rankings and ratings. Participants were provided with 40 events and 4-10 activities per event, and ranked or rated each activity's centrality or standardness. Linear mixed-effect regression showed that CheiRank, which assigns importance to activities that have many influential outgoing links, was the strongest predictor. This suggests that people's understanding of centrality relates to the degree to which an activity leads to other activities, supporting hierarchical models and the Event Horizon Model.

Keywords: Event knowledge; network science; centrality; standardness; temporal structure.

Introduction

People experience many types of events every day. A regular weekday might include events such as making breakfast, commuting to work, having lunch with colleagues, making dinner, and washing the dishes. The understanding of how these events typically unfold, and what components (e.g., activities, people, locations) are usually involved, are integral to people's event knowledge (Elman & McRae, 2019). Event knowledge plays an important role in people's lives. Many aspects of people's cognition and memory are influenced by how people think about events (Radvansky, 2012). Event knowledge also facilitates people's participation in their daily experiences (Radvansky & Zacks, 2011, 2014), enables people to understand language (McRae & Matsuki, 2009), and provides people with information so that they can think about, plan for, predict, and participate in future events (Raisig, Welke, Hagendorf, & van der Meer, 2009; Zacks & Tversky, 2001).

Events are made up of activities. For example, the event *eat at a restaurant* is made up of activities such as *make a reservation, look at the menu, order food*, *make conversation,* and *pay the bill*. A key issue in event cognition concerns the accessibility of activities given an event. That is, when people hear, read, or think about an event, what activities do they think of, and in what order do activities come to mind?

In linear theories (e.g., strong scripts; Schank & Abelson, 1977), the probability that a person thinks of an activity depends on an event's temporal structure. Activities are generated in the order in which they typically occur. Linear theories are supported by the finding that people generally agree on the temporal order of activities within events (Bower, Black, & Turner, 1979; Galambos & Rips, 1982). Furthermore, during production tasks, participants are faster to generate activities in their typical temporal order from the beginning to end, versus either in reverse temporal order or descending order of how important (i.e., central) each activity is in the event (Barsalou & Sewell, 1985). In linear theories, temporal order alone, and not importance (i.e., centrality), determines the structure of event knowledge.

In contrast, in hierarchical theories such as schemas (Ghosh & Gilboa, 2014, Rumelhart, 1980), the probability that a person thinks of an activity depends on the activity's centrality. Centrality has been characterized as an activity's importance in an event. Certain activities may be more central than others. For example, intuitively, it is more important to *eat food* during a visit to a restaurant than it is to *make a reservation*. Galambos and Rips (1982) compared how activity centrality versus temporal sequence affect participants' decisions during an event-activity verification task. Participants were presented with two activities and indicated whether or not the activities were from the same event. If event knowledge is structured linearly, then participants should respond more quickly to temporally close versus distant pairs. Instead, Galambos and Rips showed that the activities' centrality, and not temporal sequence, influenced participants' decision latencies. In hierarchical theories, centrality is unrelated to temporal sequence. In other theories, such as the Event Horizon Model (Radvansky, 2012; Radvansky & Zacks, 2014), people track the causal structure of events, which presumably relates to centrality. Memory retrieval is easier for information that participates in event-based causal relations (Lee & Chen, 2022; Radvansky, 2012).

People might also be sensitive to the frequency of occurrence of activities across individual instances of an event. For example, *order food* almost always occurs when a person *eats at a restaurant*. This dimension has been called activity standardness. In Galambos (1983), standardness was

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defined as the frequency of performing a particular activity during an event. Standardness is considered to be distinct from, but related to, centrality (Galambos, 1983; Galambos & Rips, 1982).

Activity accessibility and centrality continue to be important issues in event cognition (Raisig et al., 2009; Rosen et al., 2003). Despite centrality being a key component of these theories, questions remain about what actually underlies centrality. Originally defined as "importance" by Galambos and Rips (1982), centrality might be characterized differently based on the person's goals, context, or experience. Furthermore, some activities have dependency relations with other activities. For example, *pay the bill* depends on the completion of the activity *order food*. This relates to how feature centrality is defined in the concepts literature (for investigations of centrality and causality in object concepts such as "chair", see Ahn, Kim, Lassaline, & Dennis, 2000; Love & Sloman, 1995; Sloman, Love, & Ahn, 1998). Just as with activities within events, questions arise in the concepts literature regarding the centrality of features within object concepts. Cause-based theories of feature centrality (Ahn et al., 2000) suggest that features that have dependency relationships with other features are most central. For example, for the concept *bird*, the feature <*has wings*> is central because <*can fly*> and other features depend on it (Sloman et al., 1998). In event knowledge, dependency relationships between activities are temporally based. For the event *eating at a restaurant*, the activity *order food* might be central because activities such as *pay the bill, eat food,* and *leave the restaurant* depend on its completion. We consider this further in the Discussion.

To date, there have been limited computational measures of activity centrality within events (but see Lee & Chen, 2022). This has resulted in significant challenges for how centrality is understood in event cognition. To investigate how people think of activities given an event, the current study used network science to investigate whether network measures of centrality, all of which are based on temporal structure, can predict participant rankings and ratings of centrality and standardness.

Event Networks and Centrality

Network science, or graph theory, has been used to provide insights into multiple areas of human cognition (Siew et al., 2019). Networks contain two essential components, nodes and edges (Barabási & Pósfai, 2017; Newman, 2005). In event networks, each node corresponds to an activity (e.g., *order food*), and edges between nodes reflect the temporal relationship between each pair of activities (see Brown et al., 2024). Thus, networks can provide insights into events' temporal structure by representing temporal relations between activity pairs in the graph using directed edges. Based on edge direction, certain activities lead directly to others, but not necessarily vice versa. For example, there might be a directed edge from *order food* to *pay the bill* but not from *pay the bill* to *order food* because *order food* always occurs before *pay the bill*. All event networks used in the current study are directed (and weighted) graphs.

Brown et al.'s (2024) network model is neither hierarchical nor linear, instead capturing the rich, variable temporal structure of events. We computed five network measures of centrality: PageRank, CheiRank, 2D Rank (combination of PageRank and CheiRank), Betweenness, and Closeness. All of these measures are based on an event's temporal structure. Therefore, the present study investigated whether measures of network centrality that arise from encoding the complex temporal structure of events can predict people's rankings and ratings of activity centrality. In other words, if we computationally re-imagine how temporal structure might be processed in the human mind, can that structure predict/account for people's assessments of centrality?

PageRank, CheiRank, and 2D Rank are node-based centrality measures (Newman, 2005). These measures are based on the relationships among nodes in a network (Butts, 2009). PageRank is the original metric used by Google to rank the importance of webpages (Brin & Page, 1998; Menczer et al., 2020). PageRank can be thought of as reflecting importance through popularity. It assigns importance to nodes with many important predecessors. That is, an activity (i.e., node) with high PageRank tends to have many popular activities pointing directly to it. In contrast, CheiRank assigns importance to nodes with many important successors. In this case, CheiRank can be thought to reflect importance through influence. Thus, activities with high CheiRank tend to lead directly to many influential activities.

There also are multiple path-based measures of centrality, including Betweenness and Closeness (Bringmann et al., 2019; Siew et al., 2019). Betweenness corresponds to how often an activity is an intermediary when traversing through an event. Closeness measures an activity's communication efficiency, or the number of steps to an activity from other activities.

Figure 1 provides an example network for the event *making a sandwich*. Each node represents an activity such as *choose bread*. Node size is proportional to the activity's CheiRank, and the darkness of the arrows correspond to the edge weight. The activity with the highest CheiRank (largest node in light blue), is *choose bread*. *Choose bread* points to eight other influential activities, including *put bread on plate, choose meat,* and *choose condiments*. The node colours denote communities within the event, but this is not used in the present research. This network was constructed based on activity production data, which are described below.

The Present Study

We used the five network measures of centrality to predict people's rankings and ratings of activity centrality and standardness. The network models of event knowledge are described in detail in Brown et al. (2024). Briefly, they constructed networks for 80 common events, each of which was based on participant data from producing (e.g., "list up to 12 activities that occur in the event") or ordering (e.g., "temporally order the activities from first to last"; Hannah et al., 2022) activities for common events.

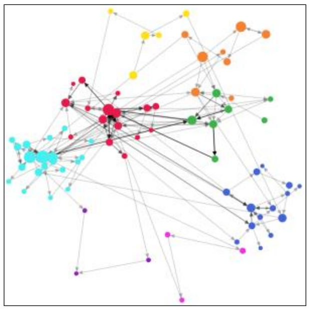


Figure 1: Event network for *making a sandwich*

For each of the 80 events, a directed edge was created from activity *i* to activity *j* if a participant indicated that activity *j* directly follows activity *i* in that event. For example, if a participant produced the activity sequence *look at the menu, order food*, and *eat food* in that order for the event *go to a restaurant,* a directed edge was created from *look at the menu* to *order food,* and from *order food* to *eat food.* However, no edge was created from *look at the menu* to *eat food* because these activities do not directly follow each other in this participant's activity sequence. If a total of *p* participants indicate that the same two activities directly follow each other in a given event, the resulting edge weight between those activities in the network was equal to *p*. If ten participants produced (or ordered) *look at the menu* immediately followed by *order food*, the resulting edge weight between these activities in the network was equal to ten. Therefore, all edge weights for a given event are between 1 and the number of participants who produced or ordered activities for the event (Brown et al., 2024).

In the present study, participants were presented with event-activity pairs from Brown et al. (2024). The dependent variables were the participants' rankings or ratings of centrality and standardness for 529 activities across 80 events. There were 10 predictors: PageRank, CheiRank, 2DRank, Betweenness, and Closeness, each from the production and ordering graphs. Linear mixed-effect regression analyses were performed to identify which network science variables predict how people think about the importance of activities within events. That is, we tested whether the event network centrality measures would predict participants' rankings and ratings of centrality and standardness.

Methods

Participants

We recruited 407 participants, 206 from the university's undergraduate participant pool in exchange for research credit, and 201 from Prolific.com in exchange for six GBP. Six participants were excluded from analyses due to limited engagement in the task. This included participants who completed less than 20% of the ranking or rating task or who were +/-3 standard deviations above or below the mean on the rating task, suggesting that these participants randomly ranked or rated the activities. The final sample included 401 participants ranging in age from 17-77 years (*M = 27, SD =13*), with 257 (64%) participants identifying as female, 136 (34%) as male (34%), and 7 (1.7%) as other (e.g., gender fluid, non-binary, intersex).

Materials

Activities from Brown et al.'s (2024) production and ordering networks were used. To select activities for the current study, we sorted the activities within each event based on descending PageRank values. Every fourth activity was used for ranking and rating. Note that although we used PageRank to select activities for the current study, PageRank did not end up predicting our centrality or standardness data. That is, PageRank did not benefit from this method of selecting activities as a predictor.

There were seven activities per event on average, ranging from 4-10. The 80 events were split into two lists, each containing 40 events. Experimenter intuition was used to place similar events in different lists so that participants were given as few similar events as possible. For example, *attending a professional baseball game* was placed in list 1, whereas *attending a professional football game* was placed in list 2. The lists were created so that all participants ranked or rated an approximately equal number of activities (292-297 total activities per list).

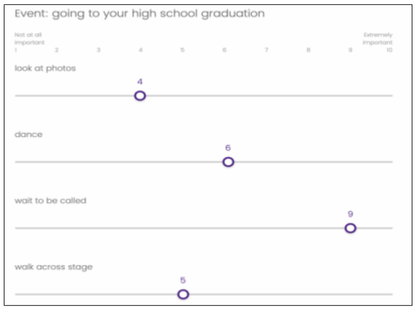
We modified Galambos and Rips' (1982) instructions. Centrality was defined to participants as the importance of the activity for performing the event. Standardness was defined in terms of the frequency with which an event would include a specific activity. In Galambos and Rips, participants ranked activities based on centrality, and rated activities based on standardness. In contrast, we collected rankings and ratings of centrality and standardness.

Procedure

The study was conducted using the online survey software, Qualtrics (Qualtrics Lab Inc., 2022). Participants completed the study on a device and in a location of their choosing. Each participant randomly received one of the two lists, and either ranked activities on centrality, rated on centrality, ranked on standardness, or rated on standardness. This resulted in 8 surveys. For centrality rating, survey A was completed by 50 participants, and survey B by 51 participants. For standardness rating, survey C was completed by 53 participants, and survey D by 52 participants. For centrality ranking, survey E was completed by 51 participants, and survey F by 44 participants. For standardness ranking, survey G was completed by 51 participants, and survey H by 51 participants.

After participants gave implied consent, they completed a demographic questionnaire. Following the demographic questions, participants read a description of either centrality or standardness, with corresponding examples. Subsequently, participants were presented with instructions which varied depending on the measure (centrality or standardness) and task (ranking or rating). Note that there was no mention of temporal order in any set of instructions.

For centrality ratings, participants rated each activity on a 1-10 scale based on the importance of the activity with regard to the event. A rating of 1 indicated that the activity was *not important at all*, whereas 10 signified that the activity was *extremely important*. For standardness ratings, participants rated each activity on a 1-10 scale based on how often the activity occurs as part of the event (frequency). A rating of 1 indicated that the activity was *not frequent at all* whereas 10 signified that the activity was *extremely frequent*. Figure 2 presents an example of the rating task.



Event: going to your high school graduation

look at photos 4

dance 6

wait to be called 9

walk across stage 5

Figure 2: A screen example of the rating task. Participants used the slider to indicate their responses.

For centrality rankings, participants ranked each activity based on its importance with regard to the event. For standardness rankings, participants ranked each activity based on the frequency of the activity in the event's occurrence. Participants dragged and dropped each activity in the order from most central (or standard) to the least. Participants were able to re-order the activities after they had been dragged to the box. Figure 3 presents an example of the ranking task.

Items
put clubs in car
hit first ball
get out of car
choose time
keep hitting ball
put clubs back in car

Playing a round of golf
1 get a caddy
2 get golf balls

Figure 3: A screen example of the ranking task. Participants dragged and dropped each activity from most to least central (or standard).

For all eight surveys, events were randomly displayed one at a time, each on a separate Qualtrics page. Participants were presented with the name of one event and a randomly ordered list of the corresponding activities. For surveys A-D, participants indicated their rating for each activity by using their mouse to move the button along a sliding scale, originally set in the middle at a rating of 5. For surveys E-H, participants indicated their ranking by using their mouse to drag the activities listed on the left side of the screen under "Items" into a box on the right side of the screen in any desired order. Following the ratings or rankings of activities for 40 events, participants received a debriefing form.

Results

Correlations Between Centrality and Standardness

Spearman correlations were calculated using the mean ranking or rating across participants for each event-activity pair. Strong positive correlations were found between centrality and standardness rankings (r = .92, p < .001) and between centrality and standardness ratings (r = .91, p < .001). Therefore, they appear to be measuring virtually the same construct in participants' minds.

Linear Mixed-Effects Regression Analyses

Linear regression analyses were conducted in *RStudio* (version 4.4.0; Posit Team, 2024) using the *lmerTest* (Kuznetsova, Brockhoff, & Christensen, 2017) and *lme4* (Bates et al., 2015) packages for linear mixed-effects models (LMEs).

The following LMEs were fitted using restricted maximum likelihood (REML). Full LMEs included the following fixed factors: CheiRank ordering, CheiRank production, PageRank ordering, PageRank production, Transformed 2D Rank ordering, Transformed 2D Rank production, Betweenness ordering, Betweenness production, Closeness ordering, and Closeness production. Random intercepts for participants and event-activity pairs were included. We used backward regression to predict participants' centrality and standardness rankings and ratings from the 10 network science centrality measures. The backward elimination method was used because it is argued to be more appropriate for LMEs (Kuznetsova et al., 2017; Zuur et al., 2009). No fixed effects were collinear according to VIF (i.e., all VIFs < 5; see Sheather, 2009). Degrees of freedom for all analyses were estimated using the Satterthwaite method.

For the ranking data, the correlations should be negative because rankings closer to 1 reflect higher centrality or standardness. On the other hand, the correlations for the rating data should be positive because higher ratings corresponded to higher centrality or standardness. That is, 1 was the lowest rating, and 10 was the highest. The regression results are presented in Tables 1 to 4.

The first result to note is that PageRank was a significant predictor of centrality ratings, and standardness ratings and rankings. However, PageRank's relationship with all four dependent variables was in the wrong direction. Therefore, we do not discuss PageRank any further.

For centrality rankings (Table 1), CheiRank ordering and production are the strongest predictors (largest t-values), with Closeness ordering and 2D Rank ordering also being significant in the correct direction. For centrality ratings (Table 2), CheiRank production is the strongest predictor, with 2DRank ordering, and Betweenness ordering and production also being significant.

For standardness rankings (Table 3), CheiRank ordering and production are the strongest predictors, with Closeness ordering also significant in the correct direction. Finally, for standardness ratings (Table 4), CheiRank production is the best predictor, with Betweenness ordering and Closeness production also significant in the correct direction. Overall, it is clear that CheiRank is the best predictor of centrality and standardness rankings and ratings.

Table 1: Centrality Rankings Backward Regression

Term	β	*SE*	*df*	*t*	*p*
Intercept	6.835	0.423	584.298	16.165	< .001*
CheiRank Ordering	–9.110	1.132	581.577	–8.045	< .001*
CheiRank Production	–3.021	0.487	581.442	–6.201	< .001*
Transformed 2DRank Ordering	–0.406	0.187	581.573	–2.169	.031*
Betweenness Ordering	1.754	0.843	581.622	2.081	.038*
Closeness Ordering	–1.016	0.255	582.323	–3.989	< .001*
Closeness Production	1.369	0.545	581.921	2.512	.012*

Note. * Indicates a significant effect at $p < .05$. All VIFs < 2.637.

Table 2: Centrality Ratings Backward Regression

Term	β	*SE*	*df*	*t*	*p*
Intercept	7.274	0.249	678.637	29.258	< .001*
CheiRank Production	2.231	0.585	582.411	3.815	< .001*
PageRank Ordering	–2.729	0.892	582.187	–3.059	.002*
Transformed 2D Rank Ordering	0.416	0.185	581.534	2.245	.025*
Betweenness Ordering	2.049	0.793	581.101	2.583	.010*
Betweenness Production	1.452	0.693	583.120	2.096	.037*

Note. * Indicates a significant effect at $p < .05$. Covariance between fixed effects is omitted. All VIFs <1.842.

Table 3: Standardness Rankings Backward Regression

Term	β	*SE*	*df*	*t*	*p*
Intercept	6.970	0.336	585.097	20.762	< .001*
CheiRank Ordering	–10.143	0.999	582.898	–10.150	< .001*
CheiRank Production	–3.804	0.422	582.705	–9.013	< .001*
PageRank Ordering	2.345	0.936	583.059	2.506	.012*
Closeness Ordering	–1.001	0.225	583.108	–4.449	< .001*
Closeness Production	1.749	0.475	582.984	3.681	< .001*

Note. * Indicates a significant effect at $p < .05$. All VIFs <1.846.

Table 4: Standardness Ratings Backward Regression

Term	β	*SE*	*df*	*t*	*p*
Intercept	7.483	0.213	678.566	35.073	< .001*
CheiRank Production	2.044	0.429	583.197	4.767	< .001*
PageRank Ordering	–2.362	0.854	583.617	–2.765	.006*
Betweenness Ordering	1.930	0.698	583.477	2.766	.006*
Closeness Production	1.241	0.458	583.349	2.712	.007*

Note. * Indicates a significant effect at $p < .05$. All VIFs <1.377.

Discussion

Event knowledge is varied and complex, which has resulted in significant challenges for researchers to characterize how event knowledge is structured in the mind (Radvansky & Zacks, 2014). Furthermore, the characterization of centrality without the use of computational models has limited our understanding of what underlies centrality. This study addressed these limitations by investigating how temporally structured event networks predict participants' rankings and ratings of centrality and standardness.

Centrality and Standardness

Our variables of centrality and standardness were highly correlated for the rankings ($r = .92$) and ratings ($r = .91$) data. This contrasts with some findings in the literature. Galambos and Rips (1982) and Galambos (1983) calculated correlations between centrality and standardness separately for each event. Correlations ranged from -.33 to .88, with a mean moderate positive correlation of $r = .39$. Based on their results, we included both centrality and standardness as dependent variables to attempt to capture these related yet distinct measures. In contrast, our data indicates that centrality and standardness are very strongly correlated.

The discrepancies between studies can be explained by differences in the selection of stimuli. Galambos and Rips (1982) discussed that during the selection of their activity-event pairs, certain activities that shared overlap within the event were removed. They provide the example of excluding activities such as *fill out the check* and *write down the date* for the event *cashing a* cheque. It is possible that the overlapping activities might have high centrality and standardness ratings. Removal of the overlapping activities may have decreased the correlation between centrality and standardness in their study. Furthermore, in Galambos (1983), the correlations between centrality and standardness might have decreased due to instances in which less central activities are nonetheless standard during an event (e.g., *counting money* for *cashing a cheque*).

Network Science Measures of Event Knowledge

Brown et al.'s (2024) network centrality measures significantly accounted for the human rankings and ratings in the current study. CheiRank was the best predictor, indicating that people's understanding of centrality can be captured by the degree to which an activity leads to other influential activities.

An activity with high CheiRank is one that is important to the unfolding of the event (centrality). For standardness, the activity occurs the most frequently during any single occurrence of the event. CheiRank is a measure of centrality that takes into account the number and influence of activities that the activity is linked to in the event network. Activities with high CheiRank values are those that point to many influential activities. Thus, people's understanding of centrality relates to the degree to which an activity leads to other influential activities.

Our finding that CheiRank was the best predictor can be viewed as supporting hierarchical models (Ghosh & Gilboa, 2014), but not linear models (Barsalou & Sewell, 1985; Bower et al., 1979). On the other hand, note that Brown et al.'s (2024) networks are not strictly hierarchical nor linear. That is, the networks are data driven in that no specific type of pre-determined data structure is posited.

Furthermore, the Event Horizon Model (Radvansky, 2012; Radvansky & Zacks, 2014) focuses on causal relationships among activities. Therefore, to the extent that CheiRank (as measured from temporal order) reflects causal dependencies, our results support the Event Horizon Model. For example, for *building a house, buy land* had the highest CheiRank value, as compared to other activities such as *hire contractor,* or *plan design*. Therefore, in some cases, highly central activities are also activities that occur near the beginning of the event (e.g., *buy land*) because later activities depend on the completion of activities that occur earlier in the event.

In the concepts literature, the centrality of an object concept's features (e.g., *has wings* as a feature of *bird*) has been measured using dependency relations (Sloman et al., 1998), which is consistent with cause-based theories (Ahn et al., 2000). A feature is considered to be central to the degree that other features depend on it. Our results support this interpretation because CheiRank reflects, at least to some degree, cause-based importance. Activities with high CheiRank point to other influential activities. Therefore, just as with central features of object concepts, activities are considered central when other activities depend on them, although for activities, dependencies are temporally based.

On the other hand, the temporal order of activities may reflect cultural conventions (e.g., the order that the courses of a meal are served and eaten), habits (the way that a specific person might proceed when they get ready for work or school in the morning), and other factors. For example, the order in which a person collects groceries might be determined by the store's layout, the person's goals, or a combination of the two. The influence of these factors can vary across events. In addition, even within a type of event, there may be sets of activities in which order primarily is causally based, and then other portions of the event in which the order of activities is much less constrained, more variable, and is due to factors other than causality. Regardless of the underlying forces that bind sequential activities, people pay attention to the temporal structure of sequences of activities around them, and it is an important aspect of event knowledge and people's ability to understand events as they unfold through time.

Surprisingly, PageRank was consistently in the wrong direction. That is, the values were positive for the rankings and negative for the ratings, and were significant for some of the variables. Therefore, a measure that captures the degree to which an activity is preceded by other popular activities (in essence, an effect activity rather than a cause activity) does not predict human centrality and standardness rankings or ratings.

Future Directions

To understand activity centrality more comprehensively, we currently are using three additional measures taken from studies of feature centrality in concepts (Sloman et al., 1998), and adapting them to measure activity centrality for events. The first is Goodness-of-example, for which it is assumed that events that include highly central activities are considered good examples, whereas examples that omit central activities are considered to be poor (e.g., "If *going camping* did not include *sleeping in a tent*, how effective of an example of *going camping* would that be?"). Second, we will use Surprise, in which people are more surprised when highly central activities are omitted from an event compared to less central ones (e.g., "How surprising would it be if *going camping* did not include *sleep in a tent*?"). The third is Prominence (e.g., "In the event *going camping,* how prominent is *sleep in a tent*?"). Our goal is to compare the predictive ability of our network centrality measures for all five centrality measures, and investigate predictive consistency (taking correlations between measures into account) to comprehensively understand centrality in event cognition.

Finally, our results were obtained from participant data during an untimed task, allowing participants time to think about their decisions before responding. Future research will use speeded paradigms (e.g., a timed event-activity verification task). Thus, we will test whether event-activity verification latency can be predicted by CheiRank.

Conclusion

We used network science measures of centrality to provide empirical and theoretical insights into what it means for activities to be central in people's event knowledge. CheiRank was the best predictor of participants' rankings and ratings, suggesting that activity centrality is determined by the degree to which an activity is followed directly in time by other influential activities. Previous theories of event knowledge have directly contrasted activity centrality versus temporal order to explain the order in which people think of activities when they hear or read the name of an event, or think about an event. In contrast, our results show that people's beliefs regarding activity central can be predicted using a computational framework that captures a richer, more complex characterization of temporal structure.

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