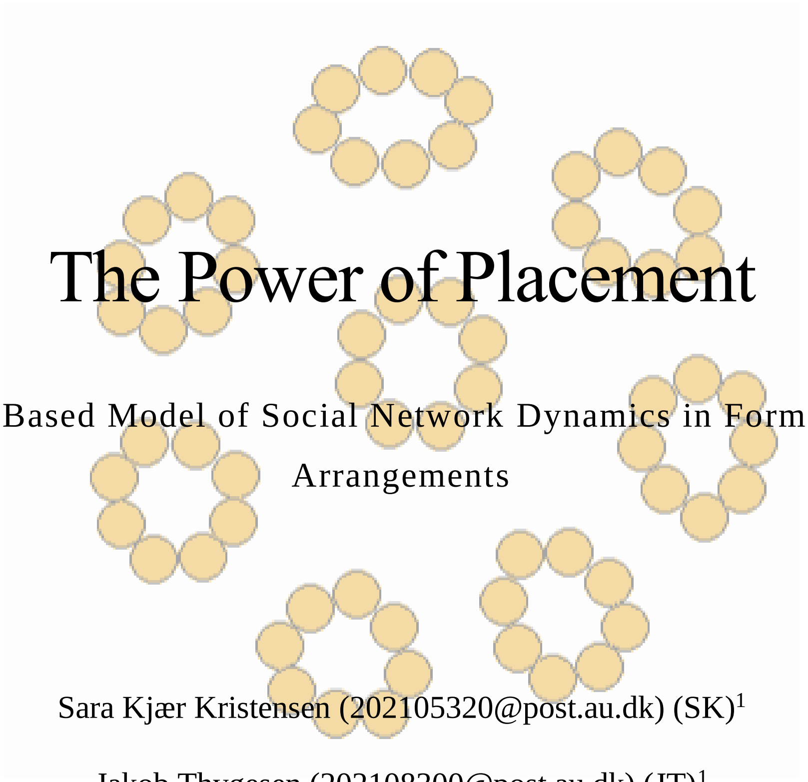

The Power of Placement

An Agent-Based Model of Social Network Dynamics in Formal Seating Arrangements

Sara Kjær Kristensen (202105320@post.au.dk) (SK)[1]

Jakob Thygesen (202108300@post.au.dk) (JT)[1]

Supervisor: Alberto Parola

Social and Cultural Dynamics

Bachelor in Cognitive Science

School of Communication and Cognition

Faculty of Arts, Aarhus University,

Jens Chr. Skous Vej 2, 8000 Aarhus, Denmark

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[1] For individual assessment sections have been marked with a responsible author corresponding to one of the authors. It is stressed that this paper is produced in strong collaboration, meaning both authors contributed to most sections, the thoughts, and work behind.

Abstract

In this paper social network dynamics are investigated using an Agent Based Model framework. The framework is grounded in Danish culture and the Investment model created by Rusbult (1980). The model simulates formal dinner party settings with a strong emphasis on the seating arrangement and table configurations. Three table configurations are established depending on how many people are within the vicinity of each other: long, square, and round tables. Throughout the simulation’s agents, later called attendees, can form and strengthen relationships. Based on the attendee's satisfaction they can choose to move throughout the party. Network measures are then compared pre- and post-party and across table configurations to determine the difference between table configurations. Results from Bayesian generalized linear models show square and round table configurations are somewhat identical but differ from round table configurations by their degree and transitivity - round tables generally have more connections between agents and are less clustered. This result is discussed to be based on the fact that at parties with round tables attendees move around 10 times as much as at parties with long and square tables. In conclusion, this paper suggests round tables for networking events and long and square tables for stable gatherings.

KEYWORDS: Agent Based Model, Bayesian, Investment Model, Network Analysis, Danish Social Events

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Notions on interactions and environments[JT]

When people interact with each other, the physical environment in which the interaction takes place plays a crucial role. Picture two friends hanging out and chatting in a mall. This conversation will most likely be different from the conversation the friends would have had, were they sitting on a couch in their living room chilling out. The topics of the conversations are in different domains. On numerous occasions, previous research has investigated how environmental factors influence social interactions and our perception of the situation we are in. To name a few, Campo et al. (2012) have shown, how the physical environment at care facilities (group sizes, location of care facility, seating possibilities in common areas, etc.) significantly influences the informal social interactions that patients with dementia have; Davis (2023) found how furniture and architectural structures influences behaviour in offices; and Totusek & Staton-Spicer (1982) showed how the location in which a student is seated in the classroom influences the learning style the student takes. Similarly, it can be assumed that the physical environment, and especially the way people are seated, at dinner parties greatly influences their perception of the party and the relationships they build during the party. This topic has only sparsely been studied – although there is a high demand for advice to people planning parties and an abundance of websites providing only weakly grounded tips (e.g., brides.com, socialtables.com). In this paper, we create an Agent Based Model (ABM) simulating different table configurations, in order to evaluate the impact of seating at dinner parties.

Relationships[JT]

People seem to have a fundamental need for relationships. As one study shows, physiological responses related to social exclusion are very similar in character to the experiences people have of physical pain (MacDonald & Leary, 2005). People often tie a big part of their identity to the social relations they engage in and gain self-esteem from the groups and relationships they believe they belong to (Crocker & Luthanan, 1990; Murphey et al., 2021). It is, therefore, no wonder the human brain – and the brain of other primates – seem to be specifically wired to prioritize social behaviour (Crosier et al., 2012; Silk, 2001). Because the advantage of acting socially vastly outweighs the disadvantages, humans have cultivated a set of behaviours which lead to collaboration and interaction.

However, people seem to engage socially for a variety of different reasons; need for affiliation, intimacy, power or control over others, lack of support in specific situations, and more (Murphey et al., 2021). Social bonds also emerge in different ways. Forsyth (2014) describes two different kinds of groups based on how they develop; "emergent groups" which come to exist spontaneously (guided by individuals being in the same physical location or over time, when people meet multiple times) and "planned groups" which are deliberately made by an external authority. Seating arrangements are per definition planned groups but do also show signs of emergent group properties since people at most parties are able to move around and break the planned groups after a certain time (i.e., often after the dinner itself has been served). Regardless of how the social interaction has started, research shows how people often are able to predict and decide the outcome of the interaction within a very short time; do I want to pursue more interaction with this person or not? (Abelson, 1976; Campbell et al., 2015; Clark et al., 2004). The underlying factors of those decisions have only been studied sparsely. Campbell et al. (2015) suggest 5 main factors influence whether a person would like to continue the interaction and further build the relationship; reciprocal candour (i.e., if you communicate well with the person and have a sense of trust towards them), mutual interest (i.e., whether you like and are interested in the same things and have the same kind of humour), personableness (i.e., whether you find the other person kind and likeable), similarity (i.e., if you share values and aspirations), and physical attraction. Interestingly Campbell et al. do not include factors about mutual acquaintances, also known as the "friend of a friend effect" in their model, although others have suggested this as a key factor (eg. Hammer, 1979; Salzinger, 1982; Stokman, 1996). This will be discussed below.

Relationships at dinner parties[JT]

The focus of this paper is on social interactions at formal dinner parties, such as weddings, larger birthday parties, galas, etc. Parties such as these share some structural properties; they are bigger events, often with more than 50 attendees, the behaviour of the attendees is structured by conventions, and a large part of the party is spent at a table eating and having conversations. When attending a formal dinner party, there has often been put thought into how people are seated and whom they sit together with. However, the people you will be sitting next to are not necessarily people you know in advance. This naturally creates a situation where new relationships can form. However, since everybody presumably has been invited to the party by the same person (the host), dinner parties have the interesting property, that regardless of whether people know each other in advance or not, everyone has at least one friend in common. This dynamic, often referred to as "the friend of a friend effect" was first considered by Heider (1946), who studied interpersonal interactions using balance theory. Heider also noted, since friends of a friend share a friend, they often have commonalities which make them more likely to also become friends.

Homophily[JT]

Just like how we tend to share interests with our close friends, we also tend to be very similar to the people we surround ourselves with on other characteristics. This is a phenomenon known as homophily. Even Aristotle and Plato considered homophily fundamental as have research established in studies of relationships (Cope & Sandys, 2010; Hackforth, 1972; McPherson et al., 2001). Homophily influences all types of relationships; marriages, friendships, work relations, etc., and concerns similarity both in ethnicity, education, interests, age, and more (McPherson et al., 2001). Dunbar (2021) also points out the more alike two people are, the more likely they are to become friends. Considering these properties of relationships, we now delve into how to formalize this knowledge into confines for our ABM.

The Investment Model[SK]

Friendships are highly cultural, and the way friendships are viewed varies greatly. To narrow down the field of research, this paper focuses specifically on social gatherings and dinner parties in Danish culture. In a survey done amongst expats by InterNations (2021), Copenhagen is ranked 54th out of 57 on the Getting Settled Index, with respondents saying "It is extremely difficult to make friends or build relationships" (*Expat Rating 2021*, 2021, p. 51). In an article in the Danish newspaper Kristeligt Dagblad (Klarskov, 2022), Danish professor in philosophy at San Jorge University in Spain, Jonas Holst, describes how Danes treasure their friendships: "In Denmark, we place a lot of importance on our friendships and perhaps because of that, we are more selective in investing energy in new relationships. So, foreigners can probably sense Danes are more selective than many others.".

This kind of attachment, where individuals cherish relationships that are long-lasting, and where people prioritize relationships they have already invested time and energy in, greatly resembles the way interactions are formalized by the Investment Model (IM) by Rusbult (1980). IM builds on the Interdependence Theory (ID), a theory originally developed by Thibaut and Kelley in 1959 and further developed in 1978 (Kelley & Thibaut, 1978).

Modelling from verbal theories[SK]

Before diving into the details of IM, it is worth considering how one might go from a verbal account of how interactions take place to a formalized model that is able to provide quantifiable predictions of interactions. IM and ID are both theories that to a large extent consist of verbal accounts combined with some mathematical formulations of key concepts. Therefore, when using IM in our ABM, the theory necessitates a great deal of consideration of how and why certain concepts are formalized (Smaldino, 2020). Some concepts have been omitted due to the scope of the paper and in order to reduce the complexity of the model. This naturally results in a simplification of the extremely complex mechanisms of social interactions. One might ask whether it is then even relevant to still study these simplified accounts. Yet for example Smaldino (2017) argues, it is exactly the simplicity of these models that makes them useful. Verbal theories are good at capturing the convoluted nature of reality. Formal models are good for making testable hypotheses, with a high level of transparency and attention to the variables which are explicitly stated. Although formal models are by no means a substitute for thorough empirical research using verbal theories, they can become an important complement to the more classical methodologies.

Comparisons and satisfaction[JT]

A core component of ID is its notion of Comparison Levels (CL) (Kelley & Thibaut, 1978). CL describes the expectations people have towards the relations they are part of. Based on prior experiences, upbringing, and observations of others, individuals comprise a CL, which will be an internal standard to evaluate interactions against. When an interaction yields outcomes that are better than what was expected based on their CL, these are experienced as satisfying and vice versa. CL can fluctuate as individuals gain new experiences, and because of this, their evaluation of a certain interaction might also change with time.

Besides CL, ID also states, that the individual estimates a comparison level for alternatives (CL-alt) (Kelley & Thibaut, 1978). This variable encapsulates the expected satisfaction the individual might gain from other relationships and is often based on an estimation of own qualities and how they might encourage or discourage other people to seek the individual. From the idea of CL-alt follows that when CL exceeds CL-alt, the individual comes to depend more and more on the person they are interacting with, since they can fulfil needs the individual has, which the individual does not expect others can fulfil.

In addition to the notion of CL, IM adds another layer to ID by taking into account the commitment one has to the relationship (Rusbult, 1980). The model assumes that the more invested you are in a relationship (i.e., how much time, money, emotional load, etc. one has invested in the relationship) the more likely you are to stay in the relationship. Furthermore, individuals are expected to invest more in relationships that have a longer expected duration, and where the investment therefore has a larger output.

Take as an example John who is lifelong friends with Mary. They have shared many wonderful times and have shown each other emotional trust. John will, according to IM, be more likely to fight to keep the friendship, than in a relationship with Carl, whom John has just met – even though John might find Carl to have more attractive personal traits than Mary. Furthermore, John will be more likely to invest time and trust in a relationship with a neighbour he believes will be staying for the next 10 years than one who will move next month.

Commitment is indirectly tied to dependence in the way people are more likely to commit to others whom they are dependent on (Rusbult et al., 1998). Therefore, if you have an interaction with a person which exceeds the expectations you have of what others might be able to provide for you, you will be more satisfied with the interaction and thereby more willing to commit to the relationship.

The workings of the Agent Based Model[JT]

An ABM is a computational model in which individual agents (in this paper representing people), their relationship with each other, and the environment in which they act is simulated (Smaldino et al., 2015). Fundamental to ABM's is the way complex behaviour can emerge from simple behavioural rules. Meaning, the rules governing the model may be straightforward, yet due to group dynamics, complex patterns of behaviour can emerge. (Smaldino et al., 2015).

The ABM created for this paper simulates participants at a dinner party. Smaldino et al. (2015) point out how ABM's typically operate on three levels; the individual level, the group level, and the structural/global level. This is also true for our model. The individual agents are simulated using various parameters based on previous literature. This includes the number of friends a person has, the interests a person has, a measure of their personality (herein extroversion), and a set of individual weightings of the importance of different variables in a relationship (i.e., how does the individual weight the importance of past relationship and homophily). To comment on the controversy of personality testing specifically when using terms such as introversion and extroversion, we point out that introversion, extroversion, or ambiversion in this paper are used to describe the social behaviour of the agents in the model, whether they are comfortable in the party setting and have high mobility. Quantifying personality has been done for many years with personality tests and individual assessments (e.g. for individual learning Schmeck & Lockhart (1983)) with varying warrant and scientific foundations (Boyle, 2008). Going forward the introvert/extrovert terms are used only in limited ways.

On the group level, we simulate different dynamics of how the interpersonal interactions work, including rules for friendship-making, interactions based on common interests, and moving around at the party. Finally, on a structural level, parties are constructed with different table configurations – round tables, square tables, and long tables limiting people's available conversation partners (see Figure 1, Methods section). This creates an environment where it is easy to compare the influence of the different table configurations and how they influence parameters on the individual and group level. The simulation will run for 20 tics, each representing half an hour in which the attendees will have the possibility to socialize with the people they sit next to. This gives a party of 10 hours, which is believed to be a reasonable timeframe for a formal dinner party.

How to quantify networks[SK]

For this paper networks are quantified using the terms degree, degree distribution, transitivity, betweenness, centrality, and eigen centrality (Baronchelli et al., 2013) to compare networks before and after the different parties. The networks are comprised of nodes and edges, where edges are weighted connections between the nodes – in this case agents. Degrees describe the number of edges per node both focal and target (i.e., going from and to the node). In these directed networks the maximum number of edges a node would have would be:

$$Number\ of\ relationships\ possible \cdot 2$$

since the edges are directed as either in- or outgoing. The degree distribution is a description of how the degrees are distributed across the network. Transitivity is also known as the clustering coefficient, which measures the probability of adjacent nodes being connected on a scale from 0 to 1. Betweenness and eigen centrality address almost the same. Betweenness evaluates the mediation effect of nodes, i.e., how often is a specific node used as a bridge between two other nodes. Eigen centrality takes the weights of edges into account, as a highly weighted node should be more crucial than a weakly weighted node. As we want to compare table configurations based on the networks they alter, we will examine the pre- and post-party networks by their degrees, clustering, and centrality terms.

Hypotheses[JT]

Based on the above-mentioned research and literature, we hypothesize an ABM will show an influence of table configuration on the interpersonal relationships and personal contentment at a formal dinner party. This will be measured by differences in degree, clustering and centrality, and number of moves.

1) It is believed seating attendees at long tables will establish fewer but stronger connections between attendees, contrary to seating attendees at round tables where attendees will establish many but weaker connections. It is believed seating attendees at square tables will yield networks in the middle ground between long and round tables.
    a. Therefore, there will be a difference in degrees and degree distribution between round tables and long tables, with round tables having the most degrees.
    b. Additionally, we will see more clustering and bounded centrality for long tables than for round tables.
2) It is also believed attendees seated at long tables will experience more contentment than attendees seated at round tables. Again, square tables will provide a middle ground.
    a. Following this, we will see that attendees will move more at parties with round tables than at parties with long tables.

Methodology

Table configuration[JT]

In this ABM, we are modelling the effect of changing the table settings at dinner parties. Therefore, 3 different types of tables are chosen, primarily based on the authors' personal experiences of commonly used table settings. As mentioned earlier, the types of tables are round, square, and long tables. Figure 1 shows how attendees of the party would be sitting at the tables. At round and square tables, 8 people will be seated, a number chosen both based on the simplicity of the setup and because it is found to be a commonly recommended table size (e.g. Martha Steward Weddings, n.d.; Milestone Event Group, 2020). The long table seats all 64 attendees at a continuous table. This also makes this table comparable to other table configurations where all attendees are seated at the same table – for instance U- shaped or E-shaped configurations.

The different tables have different properties regarding whom attendees can socialize with. This is also illustrated on Figure 1. At square tables, attendees can talk to everyone except the people sitting directly across from them – as the distance is too far for them to comfortably have a conversation. At round tables, attendees can only talk to people sitting directly beside them, as it would otherwise be discomforting for the attendee to "talk over the head" of the people sitting directly next to them, and the distance is too far for them to comfortably have a conversation with the people on the other side of the table. At long tables, attendees can socialize with the people sitting directly beside them as well as the people sitting directly across the table from them and at their diagonals, as the distance here is short enough. This means attendees can talk to 5 people when seated at a square table, 2 people when seated at a round table, and 5 people when seated at a long table (except when seated at the end of the table, where they can talk to only 3 people (version 2 of the long table)). These parameters are primarily based on personal experiences of the authors supported by literature provided e.g. by Zhu & Argo (2013).

Square formation				Round formation					Long formation						
									Version1				Version 2		
	|G|	|G|				(G)			|G|		|G|		(G)		|G|
(G)			G		|G|		|G|		(G)		|G|		|G|		|G|
|G|			G	G				G	|G|		|G|		G		G
	|G|	|G|			G		G		…		…		…		…
						G			G		G		G		G

Figure 1- table formation where letter G represents a seat and the () represents a point of view guest, where the || represents the potential conversation partners within the current tic. The three dots within the long formation represent the missing guests. The two other formations are example tables, multiple tables are simulated.

Attendee parameters[SK]

For each party, 64 attendees are simulated (among which 1 is the host of the party). All attendees are given parameters of; number of close friends, 3 personal interests, a value on the extroversion scale, weights specific for evaluating friendship score and common interests, and lastly a satisfaction baseline.

Number of close friends[SK]

Starting at the top, the number of close friends is individually sampled from a distribution of how many close friends the participants had in a survey made by Benjaminsen et al. for VIVE (see Appendix A). The distribution has 11 levels ranging from 0 to 10+ close friends. Because everyone is presumed to be friends with the host, no attendees were assigned 0 close friends. Based on the number of close friends a guest has, other attendees are randomly sampled to be friends of that guest, if the guest had more than 1 friend (the host). The host is assigned all guests as friends, giving the host 64 close friends. Every friendship created at this point will be given a relationship weight of 30.

Interests[SK]

All attendees are assigned 3 interests. The interests are drawn from a distribution of leisure time activities made by Danmarks Statistik (2022) (see Appendix B). Firstly, the host's three interests are sampled based on the probabilities given by Danmarks Statistik. The same interest can be sampled up to three times, making it possible for the host to have 1 interest taking up all 3 possible spaces. The authors deemed it reasonable that a person might be so invested in one interest, that it would account for more than one interest slot. Secondly, the guests' first interest is sampled from the three interests of the host, as we again assume the hosts' relationship to the guests builds on at least one common interest according to IM and the friend of a friend effect. The last two interests are sampled like the host's interests.

Personality traits[SK]

The attendees' personality traits regarding extroversion were conceptualized in terms of a scale from 1 to 9 with 1 being the most introverted and 9 being the most extroverted. Probabilities of the scale were adopted from a distribution based on an earlier student project (Hahn & Buchhave Søgaard, 2022). We use the extroversion term to adapt attendees' propensity to move around through the party, with extroverts being more likely to move than introverts (Eysenck, 1967). For instance, if a person John scores an 8 leaning towards being an extrovert, his threshold for moving will be set to 0.2, meaning his overall satisfaction will have had to increase by 20 percent by the end of the tic else he will try to find another seat.

Satisfaction[JT]

This leads us to discuss the satisfaction of each attendee. A baseline satisfaction is set for each attendee to account for individual differences such as having a good or bad day. This baseline is sampled from a Bernoulli distribution with a mean of 5 and a standard deviation of 2, making approximately 95% of observations fall within 1 and 9. The satisfaction of an attendee changes from tic to tic based on the number of friends the attendees can talk to in this tic (cf. Figure 1).

$$Satisfaction = Satisfaction_{baseline} + Friends\ within\ reach$$

This satisfaction term is introduced to have a simple variable to evaluate whether the agents stay seated or not, resembling the satisfaction term of ID (Kelley & Thibaut, 1978):

$$Satisfaction = CL - Outcome$$

It is out of scope for this paper to gather empirical evidence for this mechanism as we focus on relationship emergence and development.

Weightings[JT]

The last two variables are individual weightings of aspects of the interactions the attendees will take part in. Some people will weigh past relationship heavily whereas other people will weigh common interests heavily. Therefore, a ratio between the weighting of previous relationship and the weighing of common interests is drawn:

$$Weighting_{total} = Weighting_{relationship} + Weighting_{interests} = 1$$

$$Weighting_{relationship} \sim \mathcal{U}(0,1)$$

$$Weighting_{interests} = 1 - Weighting_{relationship}$$

These weightings are constant over the course of the entire party. Validating this ratio is outside the scope of this paper, however, it resembles parts of the theory provided by Rusbult (1980) in IM. With all parameters of the attendees set, we can look at how the interactions between the attendees are governed.

Interaction parameters[JT]

In terms of the interactions between the attendees, there are two key and important concepts; the commitment of the attendee and the attendee's decision on whether to move or not. These are both defined primarily based on ID and IM.

Commitment[JT]

When two attendees are sitting close to each other, both are assessing whether they want to commit to the relationship or not. This follows IM, which emphasises on the importance of the investment and commitment of the individual in the relationship. This assessment is individual, and the assessment made by one attendee does not influence the assessment of another, making the networks directed (Baronchelli et al., 2013) (i.e., the connections between attendees are not necessarily bidirectional and mutual.)

The term for commitment is taken from Rusbult (1980), and prerequisites a term for the outcome of the interaction:

$$Outcome = \sum_{i=1}^{i} w_i \cdot a_i$$

Here, a_i denotes a specific attribute of the person being interacted with, and w_i denotes the weighting of attribute *i*. In our ABM the two attributes we evaluate are the previous relationship with the person being interacted with and the number of common interests. This results in a rewritten term for outcome as:

$$Outcome = Weight_{relation} * relation\ weight + Weight_{interests} * common\ interests$$

where *relation weight* is the current weight of the relation between the two attendees and *common interests* is the number of overlapping interests two attendees has. If either of the attendees has the same interest twice, this will count as two steps on the common interests scale. Note, that since *relation weight and common interests* are on two different scales, the decision will be biased to often prioritise high outcomes towards people that the attendee has prior relationships with and therefore high relationship weights with.

IM outlines the term for commitment as

$$COM_X = O_X + I_X - O_Y$$

with COM_X being the commitment towards the person being interacted with, O_X being the outcome of the interaction with that person, I_X being the investment in that person and O_X being the alternative outcome that could have been achieved if interacting with somebody else. O_Y somewhat resembles CL-alt from ID, in the way it encapsulates probable outcomes of competing relations, but it differs by the fact that it does not take the quality of the alternative outcome into account. In our model, investment is calculated not as the investment that has already been made in another person, but as the investment that can be expected to come, as the previous investment is already included in the outcome term. Therefore, I_X is defined as

$$I_X = number\ of\ tics\ left - 1$$

O_Y is defined as the highest possible outcome amongst the people whom the person can talk to from where they are sitting.

Decision to move[SK]

After each tic, all attendees have the possibility to decide to move. This decision is based on their satisfaction in their current seat and their extroversion score. First, an attendee's threshold for moving from their seat is calculated as proportional to their introversion/extroversion score, with the threshold being on a probability scale between 0 and 1. Then the difference between current satisfaction and baseline satisfaction is computed. If the percentagewise change in satisfaction does not meet the threshold, the attendee will decide to move – if the threshold is met the attendee will stay.

Simulation[JT]

The procedure of the ABM simulation is illustrated in Figure 2. At the beginning of each tic, all the people, who do not currently have a seat – the people who decided to move at the end of the last tic - will be seated in the empty seats. When everyone is seated, it will be evaluated whether the tic is over (i.e., whether all participants have been simulated). If the tic is not over, a new attendee will be picked (from hereon referred to as the current attendee), and the simulation will be run for that attendee. Firstly, a list will be made of all the other attendees the current attendee is able to talk to within this tic. In this list, the number of common interests and the relation weight between the current attendee and the other attendees are calculated, and the current attendee decides whether to commit to a relationship with each of them. If the current attendee commits to a relationship, there will be added 1 to the current attendee's relationship weight towards this other person. If the current attendee chooses not to commit, nothing will be added to the weight.

When the new friendship commitments have been made, the current attendee assesses how many friends there are on the list of attendees it is able to talk to in this tic. From this, the satisfaction of the current attendee is calculated. Based on the calculated satisfaction and the baseline satisfaction the current attendee decides whether it wants to move or not. If the attendee decides to move, it is registered on the 'no seat'-list and will be assigned a new seat at the beginning of the next tic. This procedure is repeated for all participants for all tics.

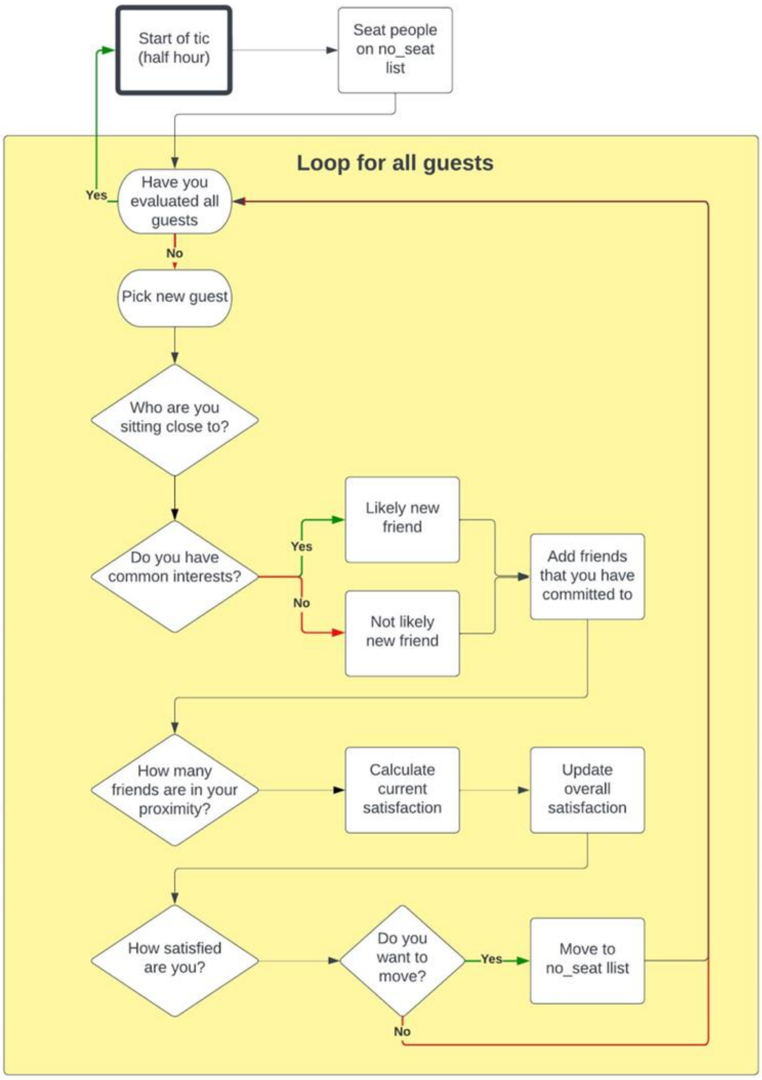


Figure 2 – flow chart of how the simulation was done.

Results and analysis

Analysis[SK]

To assess our hypotheses we make an analysis pipeline using the statistical programming language R (R Core Team, 2022). We first calculate all network measures for each table configuration through all iterations of the model both for the networks prior to the parties and after (from here referred to as the pre and post-networks) using the igraph package (Csardi & Nepusz, 2006). These measures include degrees, degree distributions, clustering coefficients, betweenness, eigen centralities, and the number of moves of an attendee. We compare the directed networks like this:

a) Pre- versus post-networks within table configurations

b) Post-networks compared across table configurations.

In order to do these comparisons, we build generalized linear models using a Bayesian framework with the R packages rstanarm and rstan (Goodrich et al., 2023; Wolfe, 2022). The models are all built with the following syntax:

$$Measure \sim table * pre/post$$

where "measure" can be degrees, degree distribution, transitivity, betweenness centrality, eigen centrality, or moves made by individuals during the party. "Table" is a factor vector with the levels congruent with the table configurations; long, round, square. Lastly the interaction term "pre/post" is to distinguish the pre- to post-party network from each other. We use default priors for all models, where stan centers and normalises predictors for normally distributed priors. The analysis of the difference between pre and post networks within table configurations is carried out primarily to validate whether the ABM works according to plan.

To investigate measurement differences between table configurations we simplify the data to only include the post-networks, as the networks prior to running the ABM are equal for all table types, and therefore exclude the interaction term for the models. Throughout the analysis, we will address the table configurations as long tables, round tables and square tables, for simplicity.

Results[SK]

In order to visually inspect the networks, a sample of networks are plotted using the igraph package for R (Csardi & Nepusz, 2006). The networks can be seen in Figure 3. It is evident the networks prior to running the model are equal – as they should be since they are created from the same criteria. The networks yielded after the ABM has run are more distinct. Here it can be seen that parties with round tables, are more interconnected, and the nodes of the network are closer together than for the long and square tables.

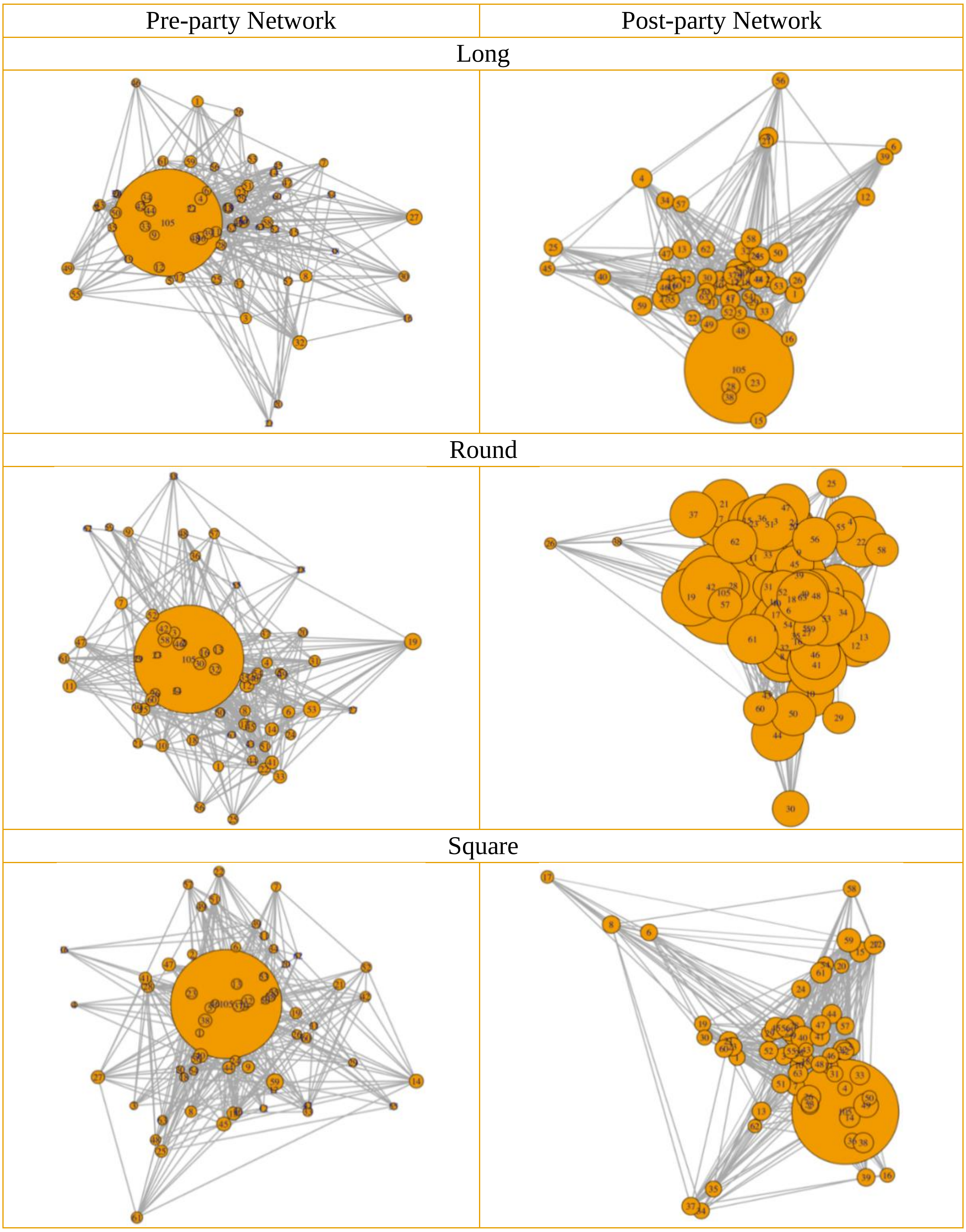


Figure 3 – Visualisations of 3 different parties, one from each table configuration. The network is plotted both before and after the party. Size of nodes represent degrees, with of edges represents relational weight.

When analysing the pre to postnetworks within table settings (a) we see both the number of edges each node has and the clustering coefficient (denoted transitivity) are different between the two networks. However, there is no difference in degree distribution, betweenness or eigen centrality when comparing postnetworks. The output of this analysis can be seen in Table 1.

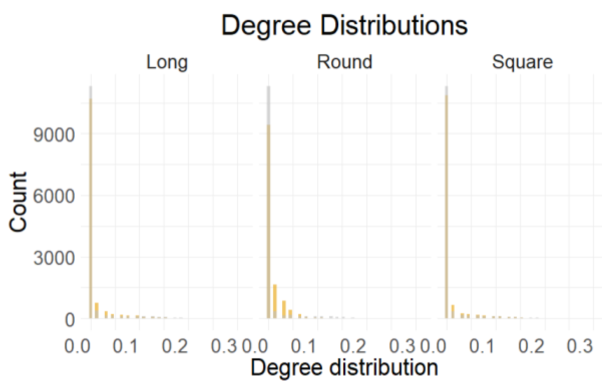
We see it is mainly the degree and transitivity that plays a role in discriminating pre- and post-party networks from one another and especially the distributions from parties with round tables differ from the long and square tables, which is also seen in the estimates.

Table	Degree	Degree distribution	Transitivity	Betweenness	Eigen Centrality
			Post-party		
Long	25.2	0.0	0.4	90.5	0.2
Round	28.7	0.0	0.1	-35.9	0
Square	-0.3	0.0	0.0	-14.2	0
			Pre-party		
Long	-11.8	0.0	-0.1	-34.4	0
Round	-28.7	0.0	-0.1	35.9	0
Square	0.2	0.0	0.0	14.3	0

Table 1 – summarized table of model estimates for the five measures. See appendix C for full model output. Note that pre-networks are relative to the post-networks.

The standard deviations are not shown in this summary output table, therefor we inspect plots to help the investigation:

Network Measures on post-party networks with pre and post network distribution marked with grey and orange respectively.



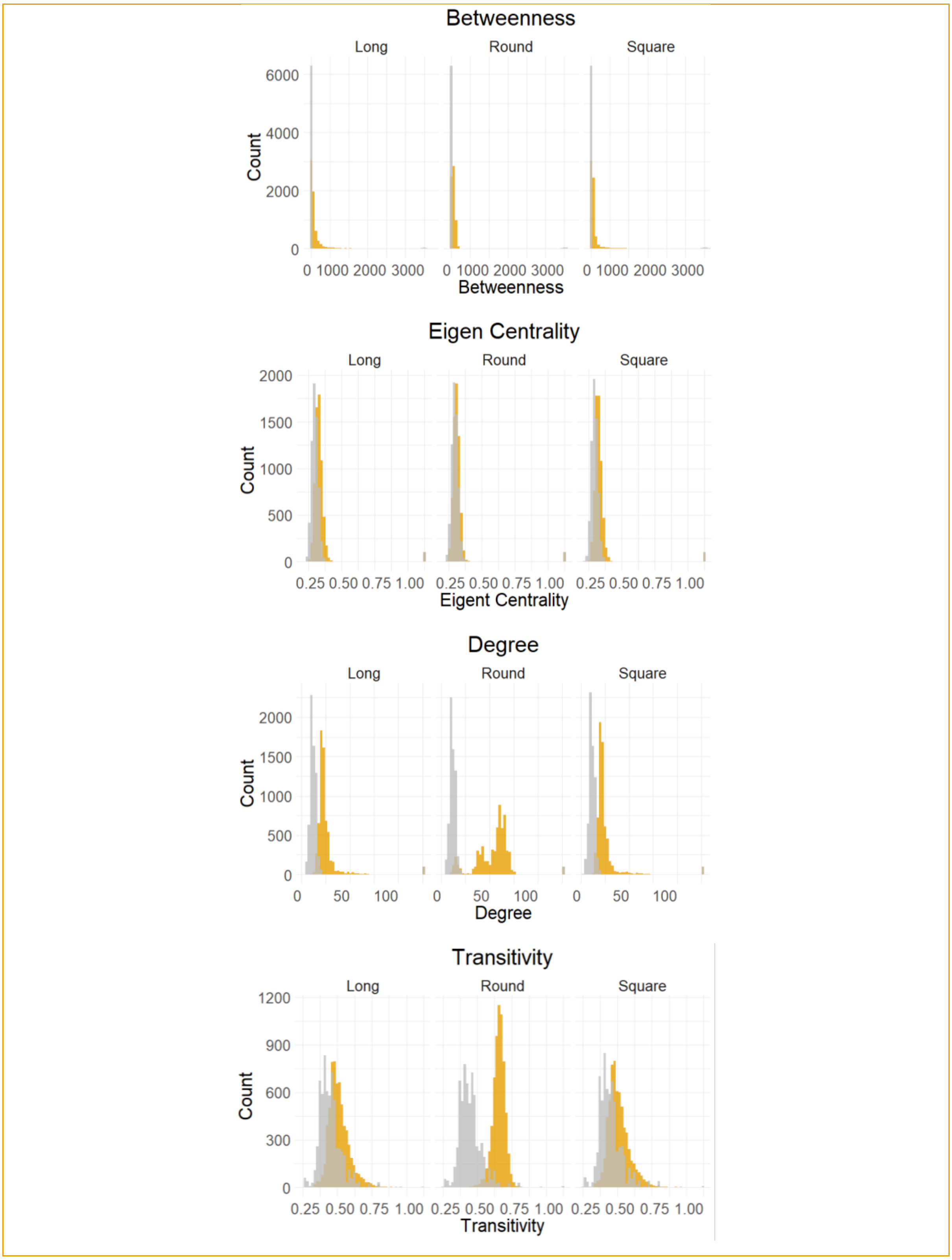


Figure 4 – The three table configurations' distribution color-coded for their respective pre- and post-party network.

When comparing post networks across table configurations (b) we again repeat each test for each iteration in the simulation. We see the same pattern of differences in network measures output (see appendix D for full overview) and will therefore take a closer look at transitivity and degrees:

Estimates	Degree	Degree distribution	Transitivity	Betweenness	Eigen Centrality
Long	25.4	0.0	0.4	91.3	0.2
Round	54	0.0	0.5	54,7	0.2
Square	24.8	0.0	0.4	76,8	0.2
Sigma	41,2	0.0	0.5	231	0.3

Table 2 - Estimates calculated from model output

The long and square tables (herein after angular tables collectively) are much more alike than hypothesized as no difference was measured above chance level. We see the same pattern in difference for the post networks of round and angular tables as we did for pre/post networks; degrees and transitivity are different from each other in close to every iteration. Moving on to the Bayesian models to find the estimates for each network measure, we first assess the models' meta parameters where we can conclude all models has an R-hat of 1 and an appropriate number of effective samples according to the number of chains and iterations[2].

Round tables differ from angular tables, because of transitivity estimate overall being 0.5 which is 25% higher than for both angular tables. Secondly, round tables are even more different from the angular tables in number of edges each node generally has (degrees) as round tables' estimate is 54 with a standard deviation of 0.5 making the estimate about twice as large as the estimates for angular tables. Since the standard deviation of all table configurations are within 0.2-0.5, we can say with much certainty they are different. The findings are visualized in figure 5.

[2] See the referenced code for in depth specification of the model and model run parameters.

Network measures on post-party networks comparing long, round and square tables

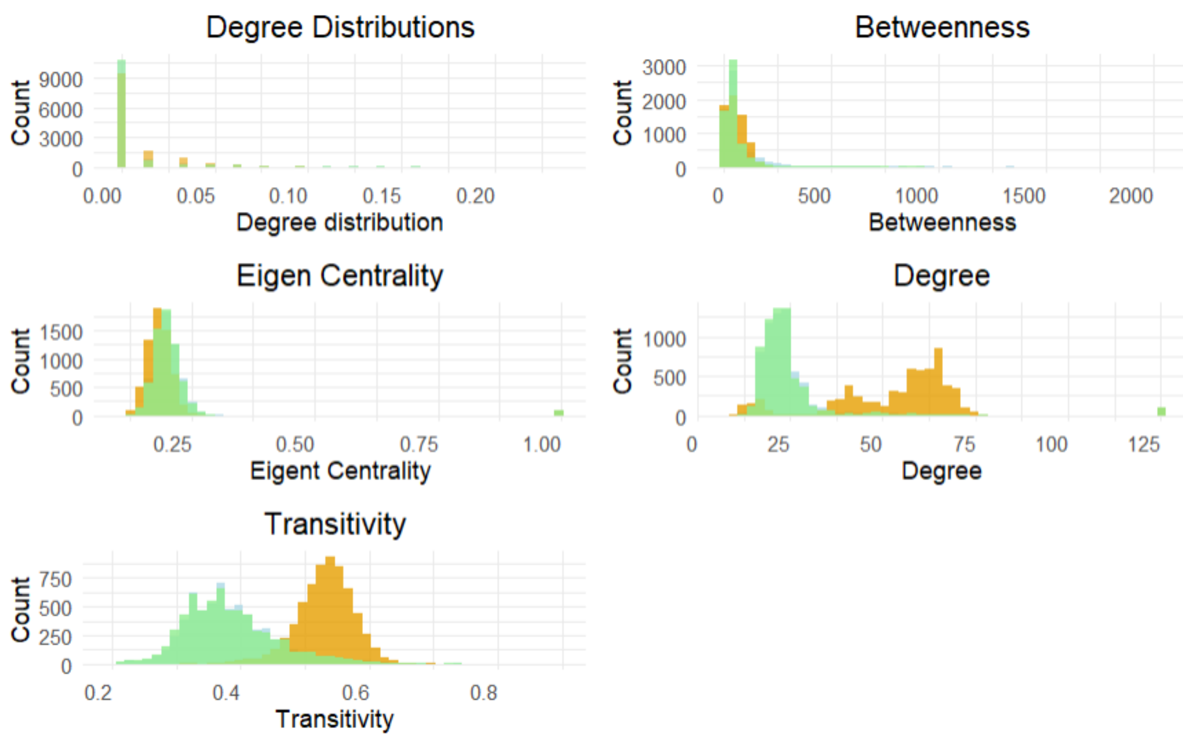


Figure 5 – plot of the five network measures comparing post-party networks for the three table configurations.

Moving on to the individual level of our simulations, we investigate the number of moves done in each iteration for each of the three table configurations.

Moves					
Estimates	Mean	sd	10%	50%	90%
Long	1.2	0.1	1.1	1.2	1.3
Round	11.1	0.2	10.8	11.1	11.4
Square	1.1	0.2	0.8	1.1	1.4
Sigma	8.0	0.1	7.9	8.0	8.2

Table 5 – Estimates calculated from model output.

The model’s estimates, which can be seen in Table 6, reveal the difference to round tables is immensely big compared to the network measures difference. Here round tables’ estimate of 11.1 is about 10 times the size of the angular tables with estimates around 1. Again, the standard deviations are small enough for us to determine this difference with certainty. Looking at the intervals for the estimates it seems most attendees at parties with round table move at least 10 times during a party, whereas the angular tables agree most people only move once if at all. We try to visualize these results with this plot:

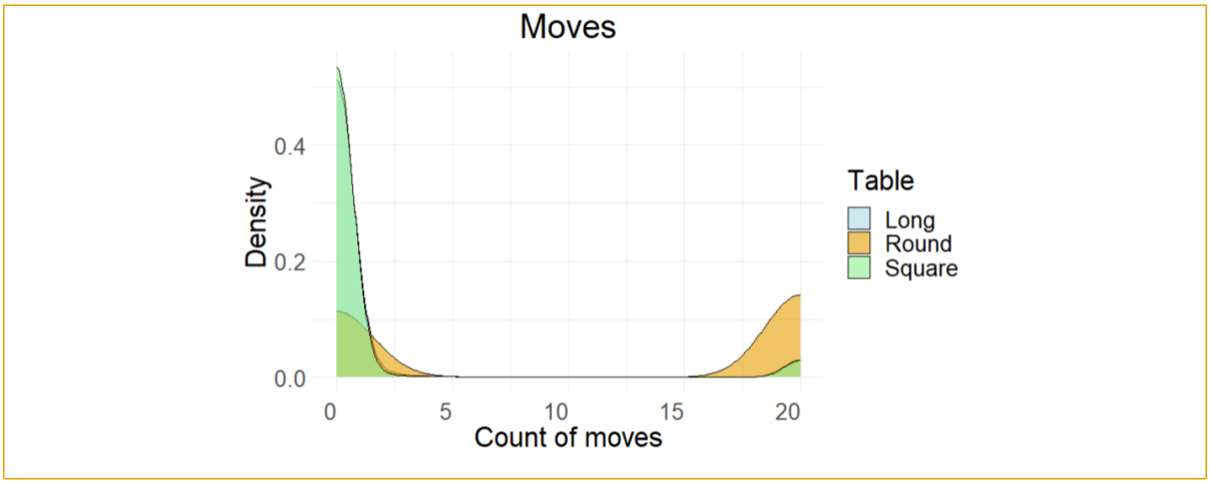


Figure 6 – plot of the moves measure comparing post-party networks for the three table configurations.[3]

Overall, we can say with certainty; angular tables are the same in both degrees, transitivity, and number of moves, whereas round tables are higher in degrees, transitivity, and number of moves.

Discussion

The evidence of the ABM[SK]

Starting at group level with hypothesis 1, we acknowledge our results only show a certain difference in degrees and transitivity, not in centrality terms or degree distribution. This leaves us to partly support hypotheses 1a and 1b. The premise of hypothesis 1 of square tables being a middle ground of comparison cannot be supported, but our results suggest square and long tables are much more alike than hypothesised. Leaving us with the last hypothesis of the attendees' movements during the party. Attendees at parties with round tables move 10 times more than for the other configurations, supporting our hypothesis 2. Overall round table configurations are with certainty different from the other table configurations.

[3] It is hard to see at first sight, but long's distribution is right beneath square's. The most obvious point of reference is to look closely at around Count of moves =1.

We suggest the reason for square tables not being a middle ground is probably because they have the same number of contact seats as the long tables, and even more so, as the square tables do not have corner seats where the attendee is limited to only 3 possible connections. Making the square and long tables basically one type of configuration. The reason for no centrality term being different in estimates is probably because everybody is already fairly interconnected at the beginning, as everyone knows the host. During the party people naturally discover each other having similar interests, as one of their interests was sampled from the host making, their propensity to become friends high.

It is worth considering if there is a better way to analyse networks, especially networks like our directed ones. The attendees' relationships were always evaluated from one point of view, meaning the propensity to form a new connection was directional and not assumed to be mutual. These networks are common as cognitivist frameworks in self-report networks. Redhead et al. (2023) argue that to find the true underlying structure of this kind of network, a Bayesian latent network approach should be adopted in order to derive the true network structure from in- and out-going edges, as this would account for the biases in participants reported relationships. Using this method, known as STRAND, the same network measurements would be investigated but based on false and true positive rates in order to compare the estimated and the reported. This method would be interesting to adopt since all our attendees have different weights for how to evaluate a relationship's outcome as described in the IM. In the code provided for this paper, you will find some of the matrices needed to fit a STRAND model. On that note we move on to the implications of these results.

Implications[JT]

Based on the results of our ABM and the analysis of the data, numerous implications become evident. This difference is based on table configurations can, of course, be beneficial since there are different purposes of social events - not all social events are created with the same motive. The objectives of a social event (i.e., the criteria for when an event is considered a success) vary greatly. At most dinner parties, like the ones within this paper's focus, the objective will often be for the attendees to have a good evening and enjoy themselves. Furthermore, it is often an objective to have guests not move too much around at the parties as thought has been put into how the seating arrangement is made. Because of this most parties will, according to our analysis, benefit from using long or square tables. Using these seems to promote a social environment, where attendees easily find other attendees whom they want to spend longer time with and build stronger connections to. We see the networks that result from these parties are more clustered and have stronger relational weights. Other social events might however have other objectives. Most business networking events tend to prioritize the ease of moving around and having many different conversations (Mandeno & Baxter, 2022). Because of this, these types of events might benefit from using round tables, which seem to promote networks wide spreading with weaker connections.

Physical environments play a role[JT]

As noted in the literature review, the physical environment in which social interactions take place does play a crucial role. This has also been shown in this investigation, where changing physical properties of the environment (the tables at the dinner parties), changed the social networks resulting from the parties.

It is, however, important to note this investigation has been carried out solely taking a Danish perspective, not accounting for cultural differences – both in how parties are conducted, and in the social and cultural norms regarding how social interactions are carried out. A wedding party will naturally look different in a middle eastern culture. Social interactions will have other governing rules in Zambia. In the famous paper "*The Weirdest People in the World"* Henrich, Heine, and Norenzayna (2010) point out how most research is done only on WEIRD (Western, Educated, Industrialized, Rich, and Democratic) societies, resulting in poor ecological validity and generalizability. This paper is guilty of the same misdeed. This limitation is of course important to remember when interpreting the results of the paper, and the authors encourage further research into the topic accounting for cultural differences.

Furthermore, this paper only sparsely takes individual differences in socialization styles into account. Research has shown there are many factors influencing how and whom you interact with as well as just random variations (e.g., Hill, 2009; Murphey et al., 2021). This is undoubtedly something that can be further studied.

Methodological considerations[JT]

As earlier touched upon, you both get and lose some when using an ABM framework. As Smaldino (2015, p. 305) says:

"Some people may be concerned that explicitly articulating every detail of a model amounts to ''setting yourself up for success.'' That is, if everything is set up according to the specifications of the theory, the only possible outcome is the one predicted by the theory. However, it is important to remember that individual-level behavioral rules do not necessarily translate directly into simple predictions of outcomes at the group level, because structural organization, feedback, and system memory all affect group-level processes. One of the strengths of ABMs is the ability to directly incorporate those properties of complex social systems, creating the potential for unexpected".

When setting up an ABM, it is important to ground choices of model parameters in previous theories and research. Throughout the design of this model, emphasis has been put on making sure the theoretical background of the ABM is sufficient. In some cases, however, this has not been possible due to the inadequacy of research in the field of seating planning.

Furthermore, ABM models are usually validated both against data from empirical research and other models in a three-step process: cross-validation against a previously validated model, sensitivity analysis, and a comparison between the ABM and output from real empirical data (Hunter & Kelleher, 2022, 2020). This has not been possible to do with this model, since there are no previously validated models available in this new field of study and no empirical data to compare to. Additionally, running a behavioural study to compare would be out of scope of this project. Therefore, we see this ABM as turning on a lamp in the dark bliss of knowledge regarding social events. When a study can be conducted it will know where to start rather than fumbling in the dark. As social events are a key phenomenon in most human cultures, we hope this paper will inspire more research.

Conclusion[SK]

To put a pin in this paper we round off with saying how using an Agent Based Model based on the Investment Model can be beneficial to investigate complex social systems. In this case, we investigated networks produced to and by parties with different table configurations and otherwise comparable. We found round table configurations to be good for making many new connections whereas angular table configurations are somewhat the same and better for more clustered parties. It is discussed how using round tables for socializing events would probably be a preferred choice and angular tables for stable seated gatherings. Taking into consideration the groundwork of the ABM, the authors suggest these results are not easily generalized to other cultures different from this WEIRD society of Denmark. As our last remark, we suggest more research is needed for this kind of investigation as it is yet to be validated and explored empirically.

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https://github.com/SAKJKR/SoCult_shared_with_the_web

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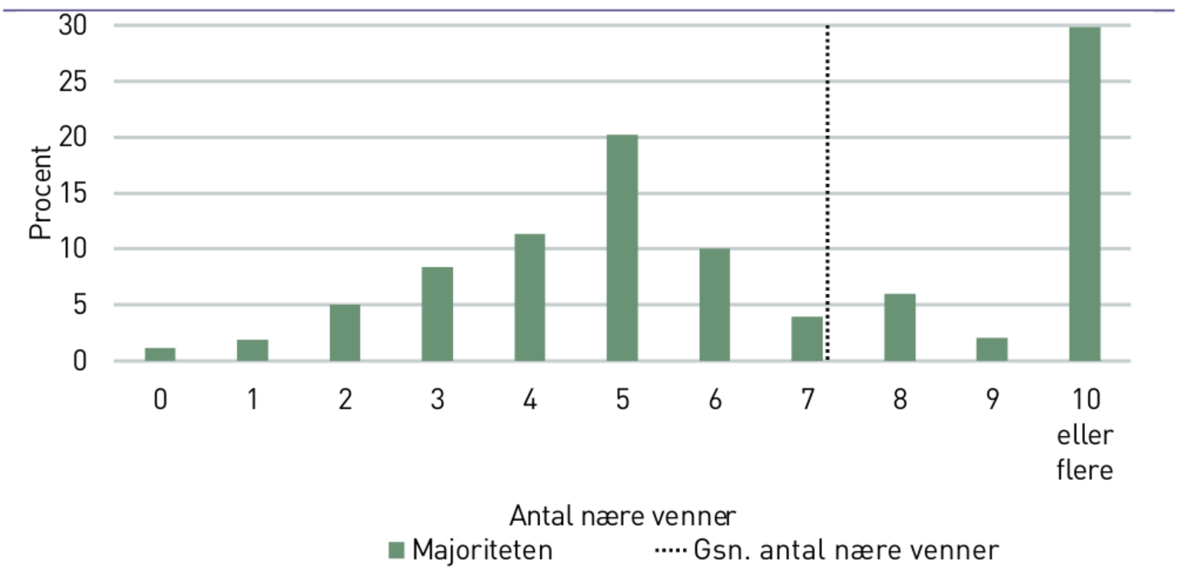
Appendices

Appendix A

From Benjaminsen et al. (2017): Fællesskabsmålingen: en undersøgelse af livsvilkår og social eksklusion i Danmark. 1430 respondents in the age og 18-80 represent this group ”Majoriteten”.

Number of close friends. Green lines denote the percentage of respondents. Dashed line denotes mean number of close friends.



Appendix B

Interest (Danish name)	English translation	Average % through the quarters of 2022
Har set film og serier + har været i biografen	Watched movies and series + been to the movies	94,75
Har lyttet til musik + har været til koncert	Listened to music + been to a concert	95,25
Har opsøgt billedkunst	Sought out visual arts	44,25
Har læst eller lyttet til skønlitterære bøger	Read or listened to factionary books	64,5
Har læst eller lyttet til faglitterære bøger	Read or listened to non-fiction books	62,5
Har spillet digitale spil	Played digital games	55
Har været (fysisk) på biblioteket	Been (physically) at the library	39
Har brugt bibliotekets digitale tjenester	Used the library's digital services	32
Har dyrket motion	Has worked out	85
Har overværet eller lyttet til en sportsbegivenhed + været til sportsbegivenhed som tilskuer	Has listened or watched a sports event + been in the audience of a sports event	74,5
Har udført frivilligt arbejde	Done voluntary work	33
Har deltaget i fritidsaktiviteter inden for de seneste tre måneder	Participated in leisure activities within the last three months	34,75
Har besøgt et museum o. lign	Visted a museum and the like	27
Har overværet scenekunst i teatret, operaen på teaterfestival eller i det offentlige rum	Attended performing arts at a theater, opera at a theater festival or in public	22,75

Appendix C

Interaction to see pre_post networks influence

Eigen centrality with interaction

```
Estimates:
                      mean   sd   10%   50%   90%
(Intercept)          0.2    0.0  0.2   0.2   0.2
tableround           0.0    0.0  0.0   0.0   0.0
tablesquare          0.0    0.0  0.0   0.0   0.0
netpre               0.0    0.0  0.0   0.0   0.0
tableround:netpre    0.0    0.0  0.0   0.0   0.0
tablesquare:netpre   0.0    0.0  0.0   0.0   0.0
sigma                0.1    0.0  0.1   0.1   0.1

Fit Diagnostics:
           mean   sd   10%   50%   90%
mean_PPD 0.2    0.0  0.2   0.2   0.2
```

Betweenness centrality

```
Model Info:
 function:     stan_glm
 family:       gaussian [identity]
 formula:      betw ~ table * net
 algorithm:    sampling
 sample:       4000 (posterior sample size)
 priors:       see help('prior_summary')
 observations: 38400
 predictors:   6

Estimates:
                      mean   sd    10%   50%   90%
(Intercept)          90.5    3.5  86.1  90.5  95.1
tableround          -35.9    4.8 -42.1 -35.9 -29.8
tablesquare         -14.2    4.9 -20.6 -14.3  -7.9
netpre              -34.4    4.9 -40.7 -34.4 -28.1
tableround:netpre    35.9    6.9  27.0  36.0  44.6
tablesquare:netpre   14.3    6.9   5.4  14.2  23.3
sigma               280.9    1.0 279.6 280.8 282.2
```

Transitivity

```
Model Info:
 function:     stan_glm
 family:       gaussian [identity]
 formula:      trans ~ table * net
 algorithm:    sampling
 sample:       4000 (posterior sample size)
 priors:       see help('prior_summary')
 observations: 38398
 predictors:   6

Estimates:
                      mean   sd   10%   50%   90%
(Intercept)          0.4    0.0  0.4   0.4   0.4
tableround           0.1    0.0  0.1   0.1   0.1
tablesquare          0.0    0.0  0.0   0.0   0.0
netpre              -0.1    0.0 -0.1  -0.1  -0.1
tableround:netpre   -0.1    0.0 -0.1  -0.1  -0.1
tablesquare:netpre   0.0    0.0  0.0   0.0   0.0
sigma                0.1    0.0  0.1   0.1   0.1
```

Degree

```
Model Info:
 function:     stan_glm
 family:       gaussian [identity]
 formula:      degree ~ table * net
 algorithm:    sampling
 sample:       4000 (posterior sample size)
 priors:       see help('prior_summary')
 observations: 38400
 predictors:   6

Estimates:
                     mean   sd    10%   50%   90%
(Intercept)         25.2    0.2  25.0  25.2  25.5
tableround          28.7    0.3  28.3  28.7  29.1
tablesquare         -0.3    0.3  -0.7  -0.3   0.0
netpre             -11.8    0.3 -12.1 -11.8 -11.4
tableround:netpre  -28.7    0.4 -29.2 -28.7 -28.2
tablesquare:netpre   0.2    0.4  -0.3   0.2   0.7
sigma               15.2    0.1  15.1  15.2  15.2
```

Degree distribution

```
Model Info:
 function:     stan_glm
 family:       gaussian [identity]
 formula:      degree_dist ~ table * net
 algorithm:    sampling
 sample:       4000 (posterior sample size)
 priors:       see help('prior_summary')
 observations: 76200
 predictors:   6

Estimates:
                      mean   sd   10%   50%   90%
(Intercept)          0.0    0.0  0.0   0.0   0.0
tableround           0.0    0.0  0.0   0.0   0.0
tablesquare          0.0    0.0  0.0   0.0   0.0
netpre               0.0    0.0  0.0   0.0   0.0
tableround:netpre    0.0    0.0  0.0   0.0   0.0
tablesquare:netpre   0.0    0.0  0.0   0.0   0.0
sigma                0.0    0.0  0.0   0.0   0.0
```

Appendix D

trans

```
Estimates:
              mean   sd   10%   50%   90%
(Intercept) 0.4    0.0  0.4   0.4   0.4
tableround  0.1    0.0  0.1   0.1   0.1
tablesquare 0.0    0.0  0.0   0.0   0.0
sigma       0.1    0.0  0.1   0.1   0.1
```

eigen

```
Estimates:
              mean   sd   10%   50%   90%
(Intercept) 0.2    0.0  0.2   0.2   0.2
tableround  0.0    0.0  0.0   0.0   0.0
tablesquare 0.0    0.0  0.0   0.0   0.0
sigma       0.1    0.0  0.1   0.1   0.1

Fit Diagnostics:
           mean   sd   10%   50%   90%
mean_PPD 0.2    0.0  0.2   0.2   0.2
```

```
Model Info:
 function:     stan_glm
 family:       gaussian [identity]
 formula:      betw ~ table
 algorithm:    sampling
 sample:       4000 (posterior sample size)
 priors:       see help('prior_summary')
 observations: 13440
 predictors:   3

Estimates:
              mean   sd    10%    50%    90%
(Intercept)   91.3    2.1   88.7   91.3   93.9
tableround   -36.6    2.9  -40.4  -36.5  -32.9
tablesquare  -14.5    3.0  -18.3  -14.5  -10.7
sigma        139.7    0.8  138.6  139.6  140.7
```

```
Model Info:
 function:     stan_glm
 family:       gaussian [identity]
 formula:      degree ~ table
 algorithm:    sampling
 sample:       4000 (posterior sample size)
 priors:       see help('prior_summary')
 observations: 13440
 predictors:   3

Estimates:
              mean   sd   10%   50%   90%
(Intercept) 25.4    0.2 25.1  25.4  25.7
tableround  28.6    0.3 28.2  28.6  29.0
tablesquare -0.6    0.3 -1.1  -0.6  -0.2
sigma       15.8    0.1 15.7  15.8  15.9
```

```
Model Info:
 function:     stan_glm
 family:       gaussian [identity]
 formula:      degree_dist ~ table
 algorithm:    sampling
 sample:       4000 (posterior sample size)
 priors:       see help('prior_summary')
 observations: 26670
 predictors:   3

Estimates:
              mean   sd   10%   50%   90%
(Intercept) 0.0    0.0  0.0   0.0   0.0
tableround  0.0    0.0  0.0   0.0   0.0
tablesquare 0.0    0.0  0.0   0.0   0.0
sigma       0.0    0.0  0.0   0.0   0.0
```