Integration of Social Network Analysis and Agent-Based Modeling Methods in the Industrial Symbiosis Context

BOYAN CHAKAROV, University of Twente, The Netherlands

Industrial Symbiosis (IS) consist of complex systems thus, structural and behavioral processes need dynamic models. The aim of this thesis is to use Social Network Analysis (SNA) as well as Agent-based Modeling (ABM) for a better understanding of the evolution of inter-firm collaboration in the IS context. The **introduction** shows why SNA's structural insights should be coupled with the actor-based model (ABM) to drive better insights than static or siloed methods. The research address the methodological gap of current IS modeling. A **systematic literature review** was performed using Scopus and identified 28 high-quality peer-reviewed studies that jointly applied SNA and ABM. A three-stage selection funnel is used in the methodology. The focus is on translating metrics, modeling trust and interaction mechanisms. The **results** for the research questions indicate that SNA measures of degree and betweenness centrality frequently find their way in the decision rules of agents in the ABM. These SNA measures determine how agents behave across the spectrum of the categories of reactive, deliberative and hybrid. The model realism of the research questions gets higher due to acceptance and trust that allow IS to have better networks. The **synthesis** section highlights that integration improves realism and strategic insights. However, the challenges are limited empirical validation, insufficient modeling of political governance layers, and frameworks varying across studies. In **conclusion**, the combination of SNA and ABM provides a more natural way to understand IS network formation in terms of structure and agency. As researchers embed trust and relational metrics into behavioral simulations, they can better inform policy, foster cooperation through time and support ecological resilience in industrial ecosystems.

Additional Key Words and Phrases: Industrial Symbiosis, Social Network Analysis, Agent-Based Modeling, Hybrid Modeling

ACM Reference Format:
Boyan Chakarov. 2025. Integration of Social Network Analysis and Agent-Based Modeling Methods in the Industrial Symbiosis Context. 1, 1 (June 2025), 8 pages.

1 Introduction

Industrial Symbiosis (IS) is in the field of circular economy a circular business model which puts out to reduce waste and improve resource efficiency by promoting interactions among industrial companies. These symbiotic relationships feature networks that can adapt and evolve. To understand IS there are required tools which are able to present structural make up of these networks and also to simulate actor behavior over time [1].

Social Network Analysis (SNA) is a tool which is used to study relationship structures in IS, which than maps out how companies interact and exchange resources [2]. There is also Agent-Based Modeling (ABM) which is to simulate individual actors' decision making processes and see how their local actions play out to produce system wide results [3, 5]. Although both of these methods are used in IS research, they are not often put together and there is no standardized framework for their integration.

This research performs a systematic review of the literature which reports on the application of SNA and ABM, aiming to identify potential improvements in the analysis of IS networks. It also examines the methodological field as a whole, report on past attempts at integration, and their advantages and challenges within IS setting [4, 6].

1.1 Problem Statement

Despite SNA and ABM gaining popularity within the contexts of sustainability and systems research, their combined use in IS seems to lag behind. The literature shows an insufficient answer concerning how these advanced methods work together concerning modeling inter-firm collaboration, resource flow exchanges, and IS networks evolution. This gap in methodology constrains the ability of researchers to explain or simulate the processes of formation, adaptation, and reactive behaviors of IS networks under external changes like policies and market shifts [7, 8].

1.2 Research Question

To fill this gap, the main research question is defined as follows:

How can the integration of Social Network Analysis and Agent-Based Modeling improve the understanding and facilitation of Industrial Symbiosis networks?

To better answer this question, the following sub-questions are formulated:

- What kind of metrics from Social Network Analysis (SNA) can be translated into behavioral rules for agents in an Agent-Based Model (ABM) of industrial symbiosis?
- How does trust and/or acceptance among firms influence the formation and/or evolution of industrial symbiosis networks in agent-based models?
- What are the advantages, challenges, and gaps in combining SNA and ABM methods in the context of IS networks formation and/or evolution?

2 Systematic Literature Review

This section explains the methods and steps to conduct a Systematic Literature Review (SLR). It describes the research synthesis approach, including the search strategy and selection criteria as well as the coding system used. The approach attempts to preserve transparency, rigor, and replicability in answering the given research questions.

2.1 Methodology

This research uses an SLR. The goal is to integrate and critique the existing scholarly work at the nexus of SNA, ABM, and IS. All

Author's address: Boyan Chakarov, b.chakarov@student.utwente.nl, University of Twente, P.O. Box 217, Enschede, The Netherlands, 7500AE.

research questions and sub-questions are answered through the analysis of peer-reviewed literature.

An SLR was conducted due to its predetermined approach that minimizes bias and enhances reliance on existing documents. Following Denyer and Tranfield's five-stage framework (problem articulation, searching, selection, extraction, synthesis, and reporting), the literature review focused on literature combining SNA and ABM in the context of IS. Only Scopus was selected because it was sufficiently multidisciplinary, had detailed TITLE-ABS-KEY indexing, and contained adequate resources relevant to the overarching thesis while being efficient to screen [41].

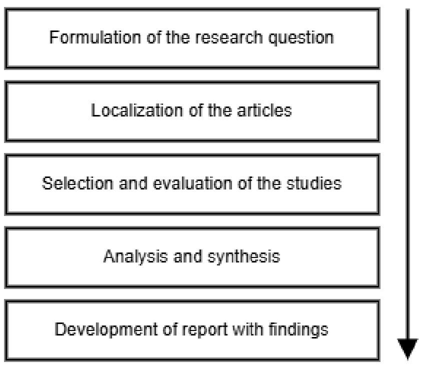

Fig. 1. **Steps of SLR by Denyer and Tranfield**

The queries which were constructed by keywords to yield the most relevant results are presented as such:

- **RQ1**: ("Social Network Analysis" OR sna) AND ("centrality" OR "structural holes" OR "community detection") AND ("Agent-Based Model*" OR abm OR "agent-based simulation" OR "multi-agent system" OR "agent simulation")
- **RQ2**: ("trust" OR "acceptance" OR "collaboration" OR "cooperation" OR "partnering" OR "mutual understanding" OR "willingness" OR "engagement") AND ("Agent-Based Model*" OR abm OR "agent-based simulation" OR "multi-agent system" OR "agent simulation") AND ("industrial symbiosis" OR "industrial ecology" OR "resource exchange" OR "waste exchange" OR "eco-industrial park")

The queries extracted **35 papers** for RQ1 and **22 papers** for RQ2. Then, a three-stage funnel was applied to further refine the results:

1. Title/abstract relevance - retained only studies that contained an SNA metric linked to an ABM (RQ1) or model trust/acceptance within an ABM (RQ2).
2. Full-text eligibility – retained peer-reviewed English articles published in journals from 2002 to 2025 that mapped the focal construct to agent behavior, excluding conference papers at this stage to maintain methodological depth and peer-review scrutiny across the sample.
3. Conceptual fit – eliminated papers where ABM was treated as background or where SNA metrics/trust appeared to be descriptive. In every article that was retained, the construct was embedded directly into the agents' decision rules.

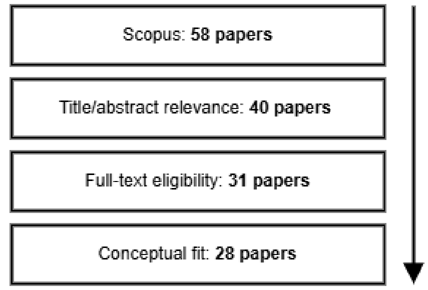

Fig. 2. **Process of selection and evaluation of literature**

Applying these criteria reduced the sets to 18 papers for RQ1 and 10 for RQ2. Each remaining study was coded with templates aligned to the research questions:

- RQ1 fields: Metric Used ⟶ Agent Rule ⟶ Behavior Type ⟶ Interaction Type
- RQ2 fields: Behavior ⟶ Decision rule ⟶ Interaction structure

Aligning search strings, eligibility filters (including the exclusion of conference papers) and extraction dimensions ensures conceptual continuity throughout the SLR pipeline and makes the subsequent synthesis directly traceable to the screening rationale.

2.2 Descriptive analysis

Conference proceedings, while useful for quickly testing emerging ideas, rarely rack up the attention journals get.Conference papers usually rely on a single citation and skip over the detailed model code, unlike journal articles that include dozens of sources and go deeper. This citation gap, reinforced the earlier decision to exclude conference items during qualitative screening.

The temporal profile of the corpus spans 2002-2025 but lean heavily toward the last few years. Roughly two-thirds are published after 2017, with noticeable spikes in 2020 and 2021 followed by a post-COVID surge of interest in network resilience and agent-based simulation. The median publication year is 2018, indicating that the evidence base is predominantly contemporary, as shown in Figure 3.

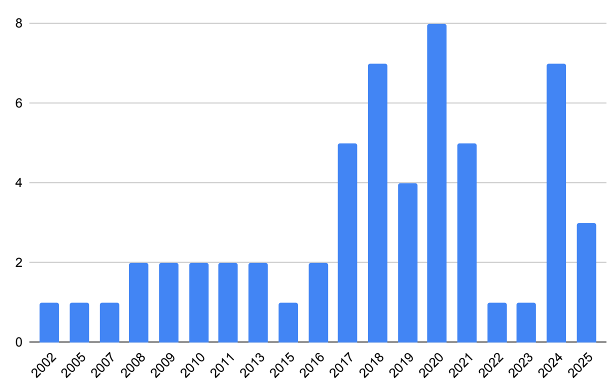

Fig. 3. Number of publications per year

2.3 Findings for Research Question 1

The eighteen journal papers that met the screening criteria can be examined through three interrelated perspectives: (i) the SNA metric applied, (ii) the incorporation of that metric within an agent's decision rule (Agent Behavior), and (iii) the overarching category of phenomena the model attempts to replicate (Behaviour Type). Analyzing the corpus along these dimensions reveals what structural information authors find important, how they operationalize it at the agent level, and what kinds of macro-behavior they ultimately investigate.

2.3.1 SNA Metric Used

Most studies gravitate toward well-established centralities because these metrics are both easy to interpret and computationally practical. Thirteen papers rely on **degree** to capture a firm's immediate resource reach, eight papers employ **betweenness** to quantify brokerage potential, five invoke **eigenvector or PageRank** for global prestige, four adopt **closeness** to model accessibility, and only two resort to **explicit structural-hole** measures like effective size or constraint. **Community-detection** appears once. The dominance of classical centralities suggests a cautious methodological culture: researchers prefer familiar metrics that are supported by standard software, even though more discriminating measures, such as brokerage or dynamic modularity, would more accurately reflect real eco-industrial-park dynamics[11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25].

In all the studies examined, centrality measures - degree, betweenness, closeness, eigenvector, and strength centrality - have proven to be essential for organizing agent behavior in ABMs derived from SNA. Each metric is capable of measuring some dimension of impact and relative importance within a network. As an example, De La Paz and Estuar et al. (2017) used degree, betweenness, and eigenvector centrality to assess the impact of media and individual agents on the public discourse regarding gender violence. These metrics enabled the ABM to model the dissemination of information based on a node's centrality in constructing the narrative, illustrating, albeit outside the IS framework, the transferable nature of the methodology[11].

In their study, Askari Sichani and Jalili et al. (2017) developed a centrality framework using degree, betweenness, and closeness to infer social power. They proved that those metrics could be applied as agent influence weights in an opinion formation model as a sophisticated estimate of the power relations between agents, even in absence of structural details. This helps to reinforce the relationship between SNA and behavioral modeling in ABMs [12].

The epidemiological studies of primate and chimpanzee disease networks further emphasize the significance of centrality. Romano et al. (2016) implemented eigenvector, strength, and betweenness centrality to assess the infection risks of Japanese macaques. Their results highlighted that central individuals not only disseminated infections more effectively but also became infected more rapidly, which emphasizes centrality's dual role as risk and transmission factor. Pierron et al. (2024) extended this work by simulating disease transmission in chimpanzees using degree, strength, and eigenvector centrality, reinforcing the association between individual centrality and epidemiological outcomes. The study stressed different centrality types (e.g., direct vs. indirect measures) were more or less predictive depending on pathogen parameters such as the infectious period [13, 17].

In the e-commerce setting, Piao et al. (2010) studied buyer-seller relationships using degree and betweenness centrality in a multi-agent simulation framework. They transformed two-mode transaction networks into one-mode projections from which they derived network centrality metrics in order to reveal hidden structures of negotiation and influence. This proved that SNA metrics could extend beyond theoretical frameworks into real-world agent simulations [23].

The combination of these studies demonstrates that SNA metrics are not only descriptive, but also constitutive elements within the designing processes of agent behavior algorithms. These measures capture as rigorous quantifiable bases to encode agent roles, risks and decision making power across various domains. Through degree showing direct connection, betweenness showing brokerage position and eigenvector showing systemic significance all serve as rigorous quantifiable bases to encode agent roles risks and decision making power across various domains[11, 13, 17, 23].

2.3.2 Agent Behavior

In ABMs pertaining to industrial symbiosis and other sociological simulations, agent behaviors are often shaped by positional metrics obtained through SNA, converting static structures into dynamic actions. A notable recurring theme across all studies is the influence of centrality on behavior. As an example, in health behavior intervention modeling by Blok et al. (2023), agents selected using in-degree, betweenness, and closeness centrality were intervened on (physically motivated) and later on influenced others through peer interactions. This behavior was akin to real-life peer modeling and diffusion phenomena in which central individuals assumed the primary propagator roles within the network [18, 19, 22, 23].

In a prior study, Shinoda et al. (2007) proposed a voting protocol in which agents picked links with utility evaluations based on centrality metrics like closeness, betweenness, or PageRank. This work demonstrated that diverse preferences of centrality yielded different network topologies which highlighted the fact that centrality was a non-spatial input to agents' algorithms for link creation and influence adjustment. In the same spirit, Piao et al. (2010) used centrality as a decision criterion in a buyer-seller networks where agents decided to accept or reject transactions given the engagement history and their position of centrality in the network. Here, centrality acted as a measure of trust and reliability, determining agents' adaptive strategies for partnership [19, 23].

Other researchers have used SNA-ABM to model social behavior and the dynamics of crisis response. Rodrigueza and Estuar (2018) studied disaster management by assigning agent roles as coordinators and connectors depending on their level of centrality in the communication network. Decisions made by agents regarding mobilization and information dissemination were based on dynamically updated belief states, knowledge states, task alignment mechanisms, and certain alignment heuristics. During emergency communication, centrally located agents acted in a dominant leadership capacity. In contrast, Abbas (2013) investigated how online friendships developed on Facebook, where agents created links according to rules of homophily — social preferences such as interest or residence — and structural geometry like mutual friendships. The agent-based simulation captured essential features of realistic network growth demonstrating the role of structural centrality together with social cognition in the development of social networks [20, 22].

The diverse cases outlined here highlight that agent behaviors, be it in diffusion of health behaviors, disaster response, formation of social ties, or negotiation in e-commerce, are fundamentally influenced by their positions in the network. Hence, centrality transcends being a mere abstract metric and becomes a functional, operational element of reasoning at the agent level decision making framework which shapes decisions such as forming links, intervening, or allocating resources. The behavioral rules embedded in these models go beyond simple reactivity. They are often proactive in nature and reflect how network topology defines possibility and limitation in social systems [18, 19, 20, 22 ,23, 25].

2.3.3 Behavior Type in ABM Translations of SNA Metrics

When adapting SNA metrics within the context of an ABM, classifying agent behaviors as reactive, deliberative, or hybrid is critical. These differences affect the realism and the degree to which the ABM can mimic intricate, emergent industrial symbiosis dynamics. Reactive behaviors stem from "signal" responses within a network, for example, collaboration gained through an increase in degree centrality. Deliberative behaviors are strategic reasoning processes that stem from a network's accumulated knowledge. Hybrid behaviors are a combination of both. Agents may act reflexively while taking into account memories or goals [11, 18, 19, 20, 25, 26].

Reactive agent behaviors have been examined in numerous studies. Rodrigueza and Estuar (2018) gave agents in a disaster response model functions such as "critical relayers" based on betweenness and degree centrality, simulating real-time response urgency. Blok et al. (2023) also modeled the dissemination of physical activity among school children through peer influence, selecting central figures using centrality criteria, which exemplifies a reactive propagation mechanism [18, 20].

Deliberative actions emerge in frameworks where agents consider centrality as a part of strategic decision making. In a voting-based ABM by Shinoda et al. (2007), agents created links based on centrality optimized utility functions applying degree and betweenness centrality, among others. Similarly, van Woudenberg et al. (2019) assessed the impact on long-term behavioral diffusion of close or betweenness centrality on agents, highlighting a more orchestrated than organic form of influence [19, 26].

The most flexibility is observed in hybrid behaviors. For example, in Simões et al. (2020) models, dairy farmers functioned as agents shaped by peer centrality (reactive) and their personal adoption thresholds (deliberative) illustrating multilayered complexity of diffusion. De La Paz and Estuar (2017) also blended immediate shifts in networks alongside changing social frames in agent responses to discourse on gendered violence illustrating the interplay of centrality and context over time [11, 25].

Ultimately, choosing a specific type of behavior will significantly influence the validity and relevance of the ABM. Reactive models are best suited for quick, localized workflows, though they tend to oversimplify complex decisions. Deliberative models are geared toward strategic planning. Hybrid models offer a balanced mixture of realism and responsiveness, making them ideal for simulation of inter-firm relations and adaptive planning in industrial symbiosis contexts [11, 18, 19, 20, 25, 26].

2.4 Findings for Research Question 2

The creation and development of industrial symbiosis networks (ISNs) rely on social elements such as trust and inter-firm acceptance, along with economic incentives. Many agent-based models (ABMs) of ISNs still work with a resource optimization and cost-benefit approach. However, trust—whether built through previous interactions, reputation, or mediation by a platform—has been shown to be vital for enduring collaboration and adaptability. The second research question investigates the impact of trust and/or acceptance on inter-firm relations and agent actions within the framework of industrial symbiosis ABMs. This question aims to demonstrate the importance of socially realistic simulations that account for social variables into the logic of modeling cooperative industrial ecosystems.

2.4.1 Behavior

In the context of ISNs, agent behavior models how firms react to economic, social, or environmental stimuli. Many models operate under the assumption that trust is irrelevant, and decisions are driven solely by cost-effectiveness or profit expectations. As an example, in Saghafi and Roshandel et al. (2024), firms "learn" the payoffs of adopting clean technologies and renegotiate contracts based on those payoffs, but their agreement is purely for economic reasons and does not involve trust. In the same way, Chen et al. (2025) model participation in wastewater treatment cooperatives with trust left out. Agents join or leave the cooperative based solely on costs [30, 36].

Unlike other studies, Ghali et al. (2017) integrates social mechanisms. They simulate firms that accumulate trust, reputation, and knowledge, which increases the likelihood of proposing or accepting symbiotic exchanges. Trust operates as a dynamic variable shaped by social interactions and previous engagements. Mollica et al. (2025) embed a trust parameter that accounts for expectations regarding the reliability of other firms participating in an industrial symbiosis platform. In this case, trust positively affects the likelihood of participation and creates feedback loops that cultivate accelerated ISN formation. Fraccascia et al. (2020) also incorporate behavioral adaptation through redundancy strategies where trust developed from historical reliability buffers against link dissolution. Batten (2009) emphasizes behavioral co-evolution showing trust is cultivated in participatory workshops and allows adversarial firms to transform into cooperative actors. Thus, across models, trust either remains absent—treated as a future research gap—or becomes a critical behavior-shaping variable that enhances cooperation, risk-taking, and network resilience over time [28, 32, 33, 34].

2.4.2 Decisions

Decision-making processes in ISN-focused ABMs range from straightforward economic calculations to complex choices moderated by social and historical variables. For instance in Yazan et al. (2018), firm decisions are based on ROI thresholds. They keep cooperation till ROI exceeds a certain mark which allows them to treat economic acceptance as a form of trust. In Yazan and Fraccascia et al. (2020)'s case, firms pay and negotiate until a certain fitness score surpassed an internal preset threshold. This continues to mount further evidence to self-centered, individualistic behavior devoid of any social structures [27, 36].

Trust often acts as a buffer and moderates decision-making frameworks. In Fraccascia et al. (2020), trust functions as inertia resisting relationship dissolutions - network stability is maintained even when profits fall. Ghali et al. (2017) explain that firms with stronger reputational capital are more inclined toward synergistic exchange, implying reputation drives participation alongside eco-profit measurement. Mollica et al. (2025) propose a two-stage decision process: firms opt to register to an online platform first, then accept or reject specific matches. Trust enhances both stages by raising the chance of beneficial relationships. Meanwhile, participatory decision-making, in which agent preferences and ABM rules merge and evolve through role-play and stakeholder feedback, is emphasized by Batten et al. (2009). Decisions are rooted in deepening interpersonal and inter-organizational trust. Taken together, these studies demonstrate that while many models still prioritize economic rationality, the addition of trust enables more resilient, cooperative, and strategically sound decisions [28, 32, 33, 34].

2.4.3 Interaction

Agent interactions in ISNs range from simple two-sided bilateral negotiations to more intricate multilateral dealings that involve brokers or platforms. Trust, more often than not, acts as the connective tissue that either facilitates or stifles connectivity. In models where there is no trust component included, interactions will be limited to a transactional nature. For instance, Saghafi and Roshandel (2024) model firm–ESCo–firm loops based on only price negotiations and adoption benefits. Chen et al. (2025) use a single wastewater treatment agent to manage participant interactions solely on the basis of operational efficiency and temporal order [30, 36].

Other models showcase more complex interaction structures, highlighting sociocultural embeddedness. Ghali et al. (2017) propose dual-layer networks: one capturing material flows and another capturing social relations, where trust and reputation influence search costs and the pace of symbiotic exchange formation. Ruiz-Puente (2021) describes the evolutionary phases of interactions: initial, intermediate, and advanced, enabled by multi-agent engagement through councils, databases, and platform-based synergy matching. In Yu et al. (2021), the link between demolition firms, recyclers, and ready-mix plants is framed as tri-partite and coordinated by a GIS-optimized broker. Trust is assumed in the platform but is not explicitly modeled, which serves as a key oversight in integrating behavioral realism [29, 34, 38].

Fraccascia et al. (2020) illustrate in greater detail how trust mitigates the effect of waste-market shocks by reducing link break-up probabilities and bolstering ISN resilience. Likewise, Batten (2009) and Mollica et al. (2025) demonstrate that interaction quality and frequency are enhanced through participatory modeling and positive trust feedback, respectively. These findings suggest that in cases where trust is modeled intentionally, agents move away from low-level, economically motivated interactions toward more robust and adaptive relations resembling the interdependence found in sustainable industrial network ecosystems [28, 32, 33].

3 Findings and Insights

This part aims to address Research Question 3 (RQ3): What is the value, problems, as well as the shortcomings of integrating SNA and ABM in consideration of the formation and/or evolution of IS networks? RQ3 is pivotal in this thesis because it captures the conclusions derived from RQ1 and RQ2 through applying synthesis analysis evaluation on the methods in question (RQ1) and utilized (RQ2). The literature selected was reviewed based on two primary criteria—advantages and challenges—to assess the effectiveness and shortcomings of the approach. These subsections provide a summary of these conclusions and examine the consequences, constraints, and gaps in research that result from the SNA-ABM integration in IS context.

3.1 Advantages

Integrating SNA and ABM creates more opportunity for in-depth understanding of the relationships as well as behaviors involved in IS networks. SNA provides a static image of inter-firm relations, useful for initializing ABMs with real-world network structures rather than random ones, improving model credibility. This was demonstrated by Fraccascia and Yazan (2019) who showed that SNA-derived key players acted as informants to agents' behaviors in the ABM simulations, improving model realism [34, 37].

Integrated frameworks have been used to study the complex impacts of a particular position in the network on innovation diffusion and the impact of network structure on system resilience. For example, Shinoda et al. demonstrated that incorporating SNA into agent rule designs can produce emergent behaviors that mimic real-world complex systems. While SNA provides static structural analysis, ABM offers dynamic change simulations. Their integration facilitates feedback modeling where behavior shapes structure and structure shapes behavior [19, 37].

Moreover, the collaborative method augments the analysis of policy scenarios. Implementing SNA metrics such as centrality within the framework of ABMs makes it possible to simulate certain actions and analyze their consequences on the entire network. This approach has been shown to aid in strategic decision-making within dynamic systems as demonstrated Rodrigueza et al (2018) [19, 20].

3.2 Challenges

Combining SNA and ABM within IS modeling has several challenges, not least of which is the availability of data. Detailed network data is often sparse, which limits the accuracy of SNA metrics and the realism of ABM initialization. Fraccascia and Yazan et al. (2020), along with many other authors, have noted that trust and transaction histories between firms are vital for calibration but extremely difficult to quantify [33].

Static SNA metrics and dynamic ABM processes pose another challenge as the two need to be aligned, resulting in one static-snapshot design choice, such as whether centrality gets recalculated at every timestep. Model behavior sensitivity, as demonstrated by Shinoda et al., impacts design choices, interpretability, and outcomes. Furthermore, simulation of large and richly connected networks incurs a significant computational load, rendering the models analytically intractable [19].

There is also an interdisciplinary dimension to consider. Effective integration requires both network analysis and agent-based modeling, which creates gaps in research teams. This can lead to behavioral assumption oversimplifications and static network use, counteracting the hybrid approach's full potential [16, 40].

3.3 Gaps

Integration of SNA and ABM within IS research is lacking in several areas, as the systematic review shows. To begin with, there are no standardized integration frameworks. The vast majority of designs only make use of SNA metrics in an ABM design in an inconsistent manner to construct some framework that 'makes' sense for the study at hand. This makes the work difficult to replicate and compare across different cases [19, 20].

Empirical validation is still an area lacking coverage. Although many models simulate some plausible behavior, very few are validated against real-world IS data, posing a challenge for external credibility [33].

The literature does not explore multi-level or multi-scalar dynamics much. Most of the IS systems cut across organizational, regional and policy domains, yet a large portion of the models are still targeted at firm-to-firm interaction. By ignoring multi-level and multi-scalar frameworks, they fail to capture systemic drivers and valuable insight regarding the large-scale development of symbiosis [19, 39].

Governance, informal collaboration and even trust are more often than not oversimplified or completely excluded. Although SNA is capable of depicting relational patterns, the rules of ABM appear to integrate very few of the richer dimensions of behavior, such as institutional incentives or cultural norms [34, 40].

4 Research Findings

In this section, the results from the Systematic Literature Review were synthesized and presented. The findings are structured according to each research question outline so that it can be shown how key concepts were put into practice, what models came forth, and which exceptional patterns still exist. All of these together provide more insight into the intersection of SNA with ABM and IS and their combining state of research.

4.1 Translation of SNA Metrics into Agent-Based Behavioral Rules (RQ1)

The review tracked a clear pattern of putting SNA scores-degree, betweenness, closeness, and eigenvector centrality-into ABMs. These metrics, often regarded as proxies for influence, access, and brokerage potential, were translated into agent behavior rules by modulating interaction preferences, influence spread, and decision pathways. Degree often served to dictate resources or peer influence, while betweenness was employed to simulate brokerage roles and information gatekeeping [11, 12, 13, 17, 23] .

Behaviors shaped by these scores sorted into three categories: reactive, deliberative, and hybrid. Reactive agents jumped on obvious network signals, such as a spike in links, while deliberative ones used SNA logic reasoning in strategic decision-making. Hybrid designs, seen in Simões et al. (2020) and De La Paz and Estuar (2017), wove short-term reactivity with long-term memory and adaptation and tweaked rules, so they captured more nuanced social dynamics and emergent phenomena in IS [11, 19, 20, 25].

4.2 Influence of Trust and Acceptance on IS Network Evolution (RQ2)

Trust and acceptance appear as key forces steering the growth of industrial symbiosis networks, though researchers model them unevenly. Some ABMs, such as those by Saghafi & Roshandel (2024) and Chen et al. (2025), stick to strictly economic logic, setting rules around cost-benefit cut-offs, while other models incorporating social dynamics demonstrated greater behavioral richness and network realism [28, 34].

Ghali et al. (2017) and Mollica et al. (2025), for example, built models where agents slowly piled up trust and let that stock guide both forming and keeping links. In their setup, trust doubles as a catalyst and a buffer:accelerated symbiotic formation in stable environments and protected existing ties under uncertain conditions. Batten (2009) took a different route with participatory modeling, showing that direct stakeholder input not only built trust quickly but also nudged agents toward steadier, less selfish behavior. Together, these studies argue that adding trust moves agent-based models away from mere static utility maximizers toward behaviorally rich, socially grounded simulations [28, 30, 34, 36].

4.3 Integration Benefits, Challenges, and Gaps (RQ3)

Putting SNA and ABM together offers significant benefits. It links the big-picture structure with everyday behavior, starts the model with realistic network initialization, and lets us track how someones role shapes what they do, and vice versa. It supports simulation of emergent IS patterns and strategic planning under policy scenarios. [19, 20, 33, 37].

However, several challenges remain. Reliable cross-company network records are still hard to find, and static SNA scores rarely capture the fluid decisions of agents. Heavy computation also slows things down, while researchers from different fields tend to use their own, often incompatible conventions. On top of that, existing studies overlook links across multi-level modeling, weak empirical validation of ABM outcomes, and treat governance, institutional norms, and cultural context as simple add-ons rather than integral drivers [20, 33, 38, 39].

5 Conclusion

The concluding segment captures the primary conclusions drawn from the review and considers their potential impact. Additionally, it emphasizes the most prominent gaps of this study and offers actionable strategies for further exploring the fusion of SNA and ABM within industrial symbiosis frameworks. Collectively, these ideas provide foundational steps toward broadening both theoretical understanding and practical engagement in this area.

5.1 Discussion

This study underscores the significant value of integrating SNA and ABM to advance the modeling and understanding of IS. When SNA scores are turned into rules for agents, each agent gains a sense of its place in the network and shows how that position shapes choices and wider results. As a result, models portray exchanges, broker roles, and diffusion of symbiotic opportunities far more realistically [11, 18, 19, 37].

Adding trust and acceptance as motives paints a fuller picture, showing that ISNs grow from shared relationships as much as from profit. Simulations that embed trust demonstrate improved resilience and adaptability, essential traits when ecological constraints and policy-driven transformations loom [28, 32, 34].

Together, these findings suggest that combining SNA and ABM creates a powerful analytical approach for exploring the complexity of IS systems, from emergent behaviors to governance and policy interventions.

5.2 Limitations

A number of constraints shaped the scope and depth of this study that were designed to maintain methodological rigor and reproducibility. As an initial step, the SLR was limited to journal literature published in peer-reviewed journals because of their upheld quality standards and academic credibility. Even though early-stage concepts from gray literature and conference abstracts could be innovative, these documents lack consistent, rigorous methodologies which make them challenging to evaluate systematically. Also, Scopus was chosen as the only database due to its extensive coverage of interdisciplinary journals with significant impact in industrial ecology, network analysis as well as simulation modeling. Although this may have disregarded some niche or regional contributions, it allowed for a streamlined and replicable search strategy. Finally, differences in how individual studies define trust or SNA measures make side-by-side comparisons tricky and broad generalizations risky [20, 33, 39, 41].

5.3 Future work

Future studies need to build clear, shared blueprints that weave social-network ideas directly into agent-based-model logic. These guides should show how static network scores become moving rules of behavior, making models easier to read and repeat [19, 38].

Models should also widen their scope to follow decision chains across many multi-level governance structures and multi-scalar interactions so it enables a clearer understanding how changes at one tier ripple through the others. Integrating empirical calibration from field studies, sensors, or company databases, will strengthen every prediction the model makes.

Lastly, because digital platforms now steer most industrial teamwork, new ABMs ought to mock up platformed ecosystems that use AI suggestions, live trust scores, and real-time negotiating tools [21, 28].

Moving forward, research should create clearer shared frameworks that incorporate social-network concepts into the logic of agent-based models to simplify the conversion of static network metrics to dynamically modeled behavioral rules which are observable and metricable.

Encompassing decision chains across multi-level governance and multi-scalar relationships will clarify how some levels' actions influence others. Several authors have insisted that this is critical for realism [32, 34]. Strengthening model validation by integrating empirical calibration with field studies, sensor data, or corporate records would enhance the credibility of model predictions and address existing gaps in validation. Lastly, platform-based ecosystems entwined with algorithmic trust scores and real-time negotiation tools await exploration in future ABMs as industrial collaboration becomes more driven by digital platforms. Ideas advanced by Mollica et al. and others serve as a foundation for such endeavors [21, 28].

6 Acknowledgments

I would like to express my sincere gratitude to Dr. Patricia Rogetzer for her invaluable guidance and encouragement throughout the course of this research. I would also like to thank Aidana Tleuken for her helpful insights and support, which greatly contributed to the development of this work.

References

[1] Ashton, W. S. (2008). Understanding the organization of industrial ecosystems. *Journal of Industrial Ecology*.
[2] Doménech, T., & Davies, M. (2011). Structure and dynamics of industrial symbiosis networks. *Resources, Conservation and Recycling*.
[3] Romero, E., & Ruiz, M. C. (2014). Framework for applying ABM in IS. *Ecological Economics*.
[4] Neves, D., Godina, R., et al. (2020). Hybrid ABM and SNA approaches to IS.
[5] Gilbert, N. (2008). *Agent-Based Models*.
[6] Wadström, C., Johansson, M., & Wallén, M. (2021). A framework for studying outcomes in industrial symbiosis. *Renewable and Sustainable Energy Reviews*, *151*, 111526.
[7] Huang, M., Wang, Z., & Chen, T. (2019). Analysis on the theory and practice of industrial symbiosis based on bibliometrics and social network analysis. *Journal of Cleaner Production*, *213*, 956–967.
[8] Morales, M. E., & Diemer, A. (2019). Industrial symbiosis dynamics, a strategy to accomplish complex analysis: The Dunkirk case study. *Sustainability*, *11*(7), 1971.
[9] Zheng, K., & Jia, S. (2017). Promoting the opportunity identification of industrial symbiosis: Agent-based modeling inspired by innovation diffusion theory. *Sustainability*, *9*(5), 765.
[10] Vahidzadeh, R., Bertanza, G., Sbaffoni, S., & Vaccari, M. (2021). Regional industrial symbiosis: A review based on social network analysis. *Journal of Cleaner Production*, *280*, 124054.
[11] De La Paz, M. M., & Estuar, M. R. E. (2017). Using social network analysis in understanding the public discourse on gender violence: An agent-based modelling approach. *Proceedings of the 2017 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM)*, 1144–1151.
[12] AskariSichani, O., & Jalili, M. (2017). Inference of hidden social power through opinion formation in complex networks. *IEEE Transactions on Network Science and Engineering*.
[13] Romano, V., Duboscq, J., Sarabian, C., Thomas, E., Sueur, C., & MacIntosh, A. J. J. (2016). Modeling infection transmission in primate networks to predict centrality-based risk. *American Journal of Primatology*, *78*, 767–779.

[14] Proskurnikov, A. V., Ravazzi, C., & Dabbene, F. (2018). Dynamics and structure of social networks from a systems and control viewpoint: A survey of Roberto Tempo's contributions. *Online Social Networks and Media*, *6*, 1–15.

[15] Piao, C., Han, X., & Zhang, S. (2009). Multi-agent modeling and analysis for e-commerce transaction network based on CAS theory. *2009 IEEE International Conference on e-Business Engineering*, 59–66.

[16] Li, F., & Lin, N. (2016). A multi-agent approach for the newsvendor problem with word-of-mouth marketing strategies. *Lecture Notes in Computer Science*, *9772*, 782–792.

[17] Pierron, M., Sueur, C., Shimada, M., MacIntosh, A. J. J., & Romano, V. (2024). Epidemiological consequences of individual centrality on wild chimpanzees. *American Journal of Primatology*, *86*, e23682.

[18] Blok, D. J., Simoski, B., van Woudenberg, T. J., & Buijzen, M. (2023). The usefulness of web-based communication data for social network health interventions: Agent-based modeling study. *JMIR Pediatrics and Parenting*, *6*, e44849.

[19] Shinoda, K., Matsuo, Y., & Nakashima, H. (2007). Emergence of global network property based on multi-agent voting model. *Proceedings of the 6th International Joint Conference on Autonomous Agents and Multiagent Systems (AAMAS)*, 66–73.

[20] Rodrigueza, R. C., & Estuar, M. R. J. E. (2018). Social network analysis of a disaster behavior network: An agent-based modeling approach. *Proceedings of the 2018 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM)*, 1100–1107.

[21] Fetta, A., Harper, P., Knight, V., & Williams, J. (2017). Predicting adolescent social networks to stop smoking in secondary schools. *European Journal of Operational Research*, *XXX*, Article in Press.

[22] Abbas, S. M. A. (2013). An agent-based model of the development of friendship links within Facebook. *Computational and Mathematical Organization Theory*, *19*(2), 232–252.

[23] Piao, C., Han, X., & Wu, H. (2010). Research on e-commerce transaction networks using multi-agent modelling and open application programming interface. *Enterprise Information Systems*, *4*(3), 329–353.

[24] Näslund, E., Näslund, E., & Näslund, C. (2019). Simulation-Based Optimization of Behavior Change Interventions for Improved Health Outcomes: A Case Study on Childhood Obesity. *Journal of Medical Internet Research*, *21*(8), e12914.

[25] Simões, A. R. P., Bueno, N. P., Almeida, F. M. S., Nicholson, C. F., Reis, J. D., & Leonel, F. P. (2020). Public policies for enhancing diffusion of technology: A network analysis for a dairy farmer community in Minas Gerais, Brazil. *Revista Brasileira de Zootecnia*, *49*, e20190207.

[26] van Woudenberg, T., Simoski, B., Fernandes de Mello Araújo, E., Bevelander, K., Burk, W., Smit, C., Buijs, L., Klein, M., & Buijzen, M. (2019). Identifying influence agents that promote physical activity through the simulation of social network interventions: Agent-based modeling study. *Journal of Medical Internet Research*, *21*(8), e12914.

[27] Yazan, D. M., Fraccascia, L., Mes, M., & Zijm, H. (2018). Cooperation in manure-based biogas production networks: An agent-based modeling approach. *Applied Energy*, *212*, 820–833.

[28] Mollica, M., Fraccascia, L., & Nastasi, A. (2025). What drives the success of online platforms for industrial symbiosis? An agent-based model. *Ecological Economics*, *230*, 108502.

[29] Yu, Y., Yazan, D. M., Bhochhibhoya, S., & Volker, L. (2021). Towards Circular Economy through Industrial Symbiosis in the Dutch construction industry: A case of recycled concrete aggregates. *Journal of Cleaner Production*, *293*, 126083.

[30] Saghafi, Z., & Roshandel, R. (2024). Agent-based simulation for technology implementation in an energy-based industrial symbiosis network. *Resources, Conservation & Recycling Advances*, *21*, 200201.

[31] Garbus, J., & Pollack, J. (2023). Emergent resource exchange and tolerated theft behavior using multi-agent reinforcement learning. *arXiv preprint arXiv:2307.01862*.

[32] Batten, D. F. (2009). Fostering industrial symbiosis with agent-based simulation and participatory modeling. *Journal of Industrial Ecology*, *13*(2), 197–213.

[33] Fraccascia, L., Yazan, D. M., Albino, V., & Zijm, H. (2020). The role of redundancy in industrial symbiotic business development: A theoretical framework explored by agent-based simulation. *International Journal of Production Economics*.

[34] Ghali, M. R., Frayret, J.-M., & Ahabchane, C. (2017). Agent-based model of self-organized industrial symbiosis. *Journal of Cleaner Production*.

[35] Nan, N., Johnston, E. W., & Olson, J. S. (2008). Unintended consequences of collocation: Using agent-based modeling to untangle effects of communication delay and in-group favor. *Computational and Mathematical Organization Theory*, *14*, 57–83.

[36] Chen, O., Mustafee, N., Evans, B., Khoury, M., Vamvakeridou-Lyroudia, L., Chen, A. S., Djordjevic, S., & Savic, D. (2025). Supporting decision-making for industrial symbioses using a hybrid modelling approach and its application to wastewater treatment. *Water Science & Technology*, *91*(5), 501–514.

[37] Yazan, D. M., & Fraccascia, L. (2019). Sustainable operations of industrial symbiosis: An enterprise input-output model integrated by agent-based simulation. *International Journal of Production Research*, *58*(2), 392–414.

[38] Ruiz-Puente, C. (2021). Proposal of a conceptual model to represent urban-industrial systems from the analysis of existing worldwide experiences. *Sustainability*, *13*(16), 9292.

[39] Akafan, M., Minaei-Bidgoli, B., & Bagheri, A. (2020). A multi-agent PSO algorithm to determine the membership percentage of each node in overlapping community in social networks. In *2020 4th Conference on Swarm Intelligence and Evolutionary Computation (CSIEC)* (pp. 037–044).

[40] Pearson, C. A. B., Singer, B. H., & Airoldi, E. (2015). Challenges to understanding covert groups. In L. M. Gerdes (Ed.), *Illuminating dark networks: The study of clandestine groups and organizations* (pp. 198–213).

[41] Denyer, D., & Tranfield, D. (2009). Producing a systematic review. In D. A. Buchanan & A. Bryman (Eds.), *The Sage handbook of organizational research methods* (pp. 671–689). Sage Publications Ltd.