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Cascading failures with group support in interdependent hypergraphs

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ABSTRACT

The functionality of an entity frequently necessitates the support of a group situated in another layer of the system. To unravel the profound impact of such group support on a system's resilience against cascading failures, we devise a framework comprising a double-layer interdependent hypergraph system, wherein nodes in one layer are capable of receiving support via hyperedges in another layer. Our central hypothesis posits that the failure may transcend to another layer when all support groups of each dependent node fail, thereby initiating a potentially iterative cascade across layers. Through rigorous analytical methods, we derive the critical threshold for the initial node survival probability that marks the second-order phase transition point. A notable finding is that as the proportion of dependent nodes increases, the dynamics of the double-layer system, characterized by Poisson hyperdegree distributions, transition from exhibiting a second-order phase transition to a first-order phase transition. In summary, our research highlights the critical role of group support mechanisms and intricate network topologies in influencing the resilience of interconnected systems with higher-order interactions against cascading failures, providing valuable insights for designing or optimizing systems to mitigate widespread disruptions and ensure sustained functionality and stability under adverse conditions.

1. Introduction

Cascading failures, characterized by the propagation of disruptions across interconnected systems, pose significant threats to various societal structures, including power grids [1–4], transportation networks [5–8], and communication systems [9–11]. These failures often originate from the malfunction of a single or a small number of entities, ultimately leading to widespread and, at times, catastrophic collapses of entire systems. Such events can disrupt critical services, cause economic losses, and even endanger human lives. Consequently, the study of cascading failures has garnered significant attention from researchers across diverse disciplines, such as physics, mathematics, computer science, and social science.

One of the fundamental approaches to studying cascading failures is through the lens of network science [12,13]. Networks provide a powerful framework for modeling and analyzing the structural properties and relationships between entities within complex systems. By representing entities as nodes and their interactions as edges, networks allow researchers to gain insights into how disruptions propagate through a system and ultimately lead to cascading failures. This network-based representation has proven to be instrumental in unraveling the underlying mechanisms that govern the resilience and vulnerability of various systems.

Furthermore, many real-world systems consist of multiple interdependent layers, where nodes and edges in one layer can depend on those in another [14–16]. This interdependence further complicates the analysis of cascading failures, as disruptions can propagate across layers, triggering failures in multiple systems simultaneously [17–19]. Furthermore, numerous researchers extended the field by introducing link direction [20], correlated properties [21,22], redundant dependencies [23], dependence strength [24–26], multiple support [27–29] to investigate the resilience of multilayer networks.

However, traditional network models that focus primarily on pairwise interactions between nodes have limitations in accurately representing real-world systems that exhibit higher-order interactions [30–32]. Higher-order interactions involve simultaneous engagements among groups comprising more than two nodes, which are prevalent in many real-world systems [33,34]. Notably, hypergraphs provide a more comprehensive framework to model various complex systems for modeling complex systems, capturing the richness and diversity of higher-order interactions due to the fact that hyperedges can connect an arbitrary number of nodes [35,36].

Despite the growing acknowledgment of the importance of higher-order interactions and interdependencies in complex systems, research on cascading failures in interdependent hypergraphs remains relatively limited [37–40]. Notably, most existing studies focus primarily on the dependencies between nodes across different layers, often overlooking the potential for nodes to also depend on various hyperedges (support

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groups) in another layer. In many systems, individual nodes rely on specific groups to access vital resources or information. In financial networks, companies often rely on industry associations to manage market risks collectively. For example, a group of banks may depend on an industry association to monitor market fluctuations and coordinate risk management strategies. If the industry association fails (e.g., due to regulatory issues), the banks may lose access to critical information and support, leading to individual failures that can cascade across the financial network. In supply chains, individual companies may depend on supplier groups for raw materials and components. For example, an automobile manufacturer may rely on a group of suppliers for parts and components. If a supplier group fails (e.g., due to a natural disaster or economic downturn), the manufacturer may experience delays and production disruptions, leading to cascading failures across the supply chain. In transportation networks, individual logistics teams may depend on coordination groups for scheduling and resource allocation. For example, a shipping company may rely on a logistics team to coordinate shipments and manage resources. If the logistics team fails (e.g., due to a lack of coordination or resource shortages), the shipping company may experience delays and operational disruptions, leading to cascading failures across the transportation network.

To address this gap, we propose a simplified framework to study cascading failures in interdependent hypergraphs. Our model comprises two mutually dependent hypergraphs, incorporating the concept of support groups where nodes in one hypergraph rely on hyperedges in the other for functionality. By capturing both higher-order interactions and interdependencies between nodes and hyperedges across layers, our model offers a more accurate and comprehensive representation of real-world complex systems, enabling a deeper investigation into how failures propagate across the double-layer system.

2. The model

We construct a double-layer interdependent hypergraph system, denoted as A and B, comprising N_A and N_B nodes, and M_A and M_B hyperedges, respectively. Each node's hyperdegree, represented by k, indicates the number of hyperedges it is part of. The hyperdegree distributions for layers A and B are denoted as $P_A(k)$ and $P_B(k)$. Similarly, the cardinality m of a hyperedge, which is the count of nodes it encompasses, adheres to distributions $Q_A(m)$ and $Q_B(m)$.

Our model integrates interdependencies where nodes in one layer rely on support hyperedges from the other. Specifically, a node in layer A is chosen with probability q_A to depend on support hyperedges from layer B, and similarly for nodes in layer B with probability q_B. The support degree of each dependent node (i.e., the number of support hyperedges), denoted as $\tilde{k}$, follows distributions $\tilde{P}_A(\tilde{k})$ and $\tilde{P}_B(\tilde{k})$.

The cascading dynamics commence with the removal of nodes with probabilities $1 - r_A$ and $1 - r_B$ in each respective layer, where r represents the initial node survival probability. Subsequently, a node remains functional only if: (i) it is connected to at least one functional support hyperedge in the other layer; and (ii) it is part of the Giant Connected Component (GCC) within its own layer, ensuring internal connectivity. This cascading failure process, triggered by the initial node removals, iterates between the two layers until no additional nodes fail. The size of the final GCC for layers A and B is denoted as S_A and S_B, respectively. In the following sections, we exclusively analyze symmetric cases, where the resilience of the double-layer system can be assessed by the size S of the GCC in either layer, i.e., $S_A = S_B = S$.

The cascading failure process within the model can be illustrated in Fig. 1. Initially, nodes 6 and 7 in layer A, along with node 3 in layer B, are removed. At stage 1 of layer A, the hyperedge e_3 collapses, which consequently causes the small component consisting of hyperedges e_4 and e_5 to collapse as it detaches from the GCC. At stage 1 in layer B, node 4 will fail due to the collapse of its support hyperedges e_3 and e_4 in layer A, and node 8 will fail due to the collapse of its only support hyperedge e_4 in layer A as well. Furthermore, the collapse of hyperedge e_2 in layer B, leading to the collapse of the small component that comprises hyperedge e_1, as it is disconnected from the GCC of layer B. Finally, node 3 in layer A fails due to the collapse of its support hyperedges e_1 and e_2. The cascading failure process ceases as no further nodes fail. The final GCC is composed of the component of nodes $\{1,2,4,5,11\}$ in layer A, and the component of nodes $\{5,6,7,9,10\}$, respectively.

3. Key results

To characterize the structures and interdependencies of both layers, we introduce several generating functions. These functions encapsulate essential information regarding the distributions of hyperdegrees, cardinalities within each layer, and support degrees across layers. The generating functions for the hyperdegree distribution are defined as

$$\begin{cases} G^A_{k0}(x) = \sum_{k=0}^{\infty} P^A(k)x^k, \\ G^B_{k0}(x) = \sum_{k=0}^{\infty} P^B(k)x^k. \end{cases} \tag{1}$$

The generating functions for the excess hyperdegree distribution are defined as

$$\begin{cases} G^A_{k1}(x) = \sum_{k=1} \frac{kP^A(k)}{\langle k\rangle} x^{k-1} = G^{A\prime}_{k0}(x)/G^{A\prime}_{k0}(1), \\ G^B_{k1}(x) = \sum_{k=1} \frac{kP^B(k)}{\langle k\rangle} x^{k-1} = G^{B\prime}_{k0}(x)/G^{B\prime}_{k0}(1). \end{cases} \tag{2}$$

The generating functions for the support degree distribution are defined as

$$\begin{cases} \tilde{G}^A_{k0}(x) = \sum_{k=0}^{\infty} \tilde{P}^A(k)x^k, \\ \tilde{G}^B_{k0}(x) = \sum_{k=0}^{\infty} \tilde{P}^B(k)x^k. \end{cases} \tag{3}$$

The generating functions for the cardinality distribution are defined as

$$\begin{cases} G^A_{m0}(x) = \sum_{m=0}^{\infty} Q^A(m)x^m, \\ G^B_{m0}(x) = \sum_{m=0}^{\infty} Q^B(m)x^m. \end{cases} \tag{4}$$

The generating functions for the excess cardinality distribution are defined as

$$\begin{cases} G^A_{m1}(x) = \sum_{m=1} \frac{mQ^A(m)}{\langle m\rangle} x^{m-1} = G^{A\prime}_{m0}(x)/G^{A\prime}_{m0}(1), \\ G^B_{m1}(x) = \sum_{m=1} \frac{mQ^B(m)}{\langle m\rangle} x^{m-1} = G^{B\prime}_{m0}(x)/G^{B\prime}_{m0}(1). \end{cases} \tag{5}$$

As illustrated in Fig. 1, the cascading failure process unfolds in discrete iterations, progressing from stage $n = 1$ to $n = \infty$ within both layers.

We denote the probabilities that hyperedges are functional in layers A and B at stage n as T^A_n and T^B_n, respectively. Consequently, the probability that a dependent node in layer $A(B)$ at stage n lacks functional support hyperedges in layer $B(A)$ is given by

$$\begin{cases} u^A_n = \sum_{k=0}^{\infty} \tilde{P}^A(k)\left(1 - T^B_{n-1}\right)^k = \tilde{G}^A_{k0}(1 - T^B_{n-1}), \\ u^B_n = \sum_{k=0}^{\infty} \tilde{P}^B(k)\left(1 - T^A_{n-1}\right)^k = \tilde{G}^B_{k0}\left(1 - T^A_{n-1}\right). \end{cases} \tag{6}$$

The fraction of nodes in layer $A(B)$ which remain functional at stage n after applying condition (i) is derived as

$$\begin{cases} p^A_n = r^A\left(1 - q^A u^A_n\right), \\ p^B_n = r^B\left(1 - q^B u^B_n\right). \end{cases} \tag{7}$$

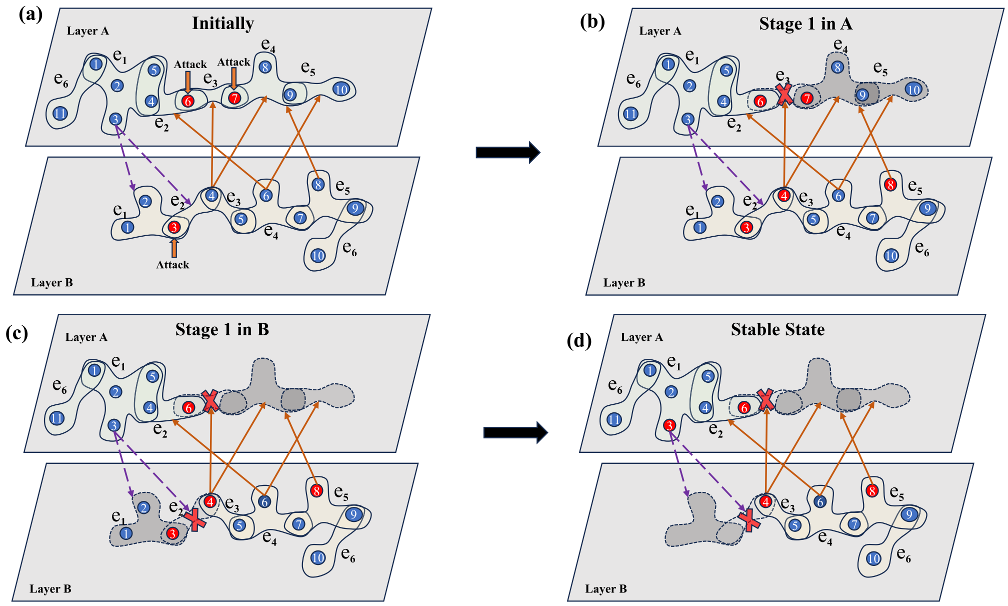

Fig. 1. Illustration of a cascading failure process within double-layer hypergraphs A and B. Arrow lines signify the interdependencies established between dependent nodes in one layer and their respective support hyperedges in the other layer. Blue nodes indicate functional nodes, contrasting with red nodes, which signify failed nodes. Hyperedges depicted in gray symbolize those that have collapsed due to their disconnection from the Giant Connected Component (GCC), whereas hyperedges marked with red crosses represent failures directly attributed to the collapse of their constituent nodes. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Subsequently, the probabilities T_n^A and T_n^B are expressed as

$$\begin{cases} T_n^A = \sum\limits_{m=0} Q^A(m) \sum\limits_{j=0}^{m} \binom{m}{j} \left\{1-[G_{k1}^A\left(1-f_n^A\right)]^{m-j}\right\} (p_n^A)^{m-j}\left(1-p_n^A\right)^j, \\ T_n^B = \sum\limits_{m=0} Q^B(m) \sum\limits_{j=0}^{m} \binom{m}{j} \left\{1-[G_{k1}^B\left(1-f_n^B\right)]^{m-j}\right\} (p_n^B)^{m-j}\left(1-p_n^B\right)^j, \end{cases} \tag{8}$$

where f_n^A or f_n^B represents the probability that a randomly selected hyperedge, reached through a random node, can connect to the GCC of each layer (condition (ii)). First, choose a random hyperedge with cardinality m according to the distribution $Q^A(m)$ or $Q^B(m)$. Then, $\binom{m}{j}$ represents the scenario where there are j failed nodes among the m nodes in the selected hyperedge. The term $1-[G_{k1}^A\left(1-f_n^A\right)]^{m-j}$ or $1-[G_{k1}^B\left(1-f_n^B\right)]^{m-j}$ denotes the probability that within a random hyperedge of cardinality m, at least one node out of $m-j$ functional nodes along the remaining hyperedges can connect to the GCC.

Analogously, we can derive f_n^A and f_n^B as

$$\begin{cases} f_n^A = \sum\limits_{m=1} \dfrac{mQ^A(m)}{\langle m\rangle} \sum\limits_{j=0}^{m-1} \binom{m-1}{j} \left\{1-[G_{k1}^A\left(1-f_n^A\right)]^{m-1-j}\right\} \\ \qquad \times (p_n^A)^{m-1-j}\left(1-p_n^A\right)^j, \\ f_n^B = \sum\limits_{m=1} \dfrac{mQ^B(m)}{\langle m\rangle} \sum\limits_{j=0}^{m-1} \binom{m-1}{j} \left\{1-[G_{k1}^B\left(1-f_n^B\right)]^{m-1-j}\right\} \\ \qquad \times (p_n^B)^{m-1-j}\left(1-p_n^B\right)^j. \end{cases} \tag{9}$$

Therefore, the fractions S_n^A and S_n^B of nodes in the GCC can be obtained by

$$\begin{cases} S_n^A = p_n^A[1-G_{k0}^A(1-f_n^A)], \\ S_n^B = p_n^B[1-G_{k0}^B(1-f_n^B)]. \end{cases} \tag{10}$$

Upon termination of the cascading failure process, p_n^A, p_n^B, T_n^A, T_n^B, f_n^A, f_n^B, S_n^A, and S_n^B all converge to their steady values p_∞^A, p_∞^B, T_∞^A, T_∞^B, f_∞^A, f_∞^B, S_∞^A, and S_∞^B, respectively.

Based on the generating functions of Eqs. (4) and (5), the steady values of T_∞^A from Eq. (8) and f_∞^A from Eq. (9) can be simplified into

$$\begin{cases} T_\infty^A = 1-G_{m0}^A\left(1-p_\infty^A+p_\infty^A G_{k1}^A\left(1-f_\infty^A\right)\right), \\ f_\infty^A = 1-G_{m1}^A\left(1-p_\infty^A+p_\infty^A G_{k1}^A\left(1-f_\infty^A\right)\right). \end{cases} \tag{11}$$

Similarly, we can obtain

$$\begin{cases} T_\infty^B = 1-G_{m0}^B\left(1-p_\infty^B+p_\infty^B G_{k1}^B\left(1-f_\infty^B\right)\right), \\ f_\infty^B = 1-G_{m1}^B\left(1-p_\infty^B+p_\infty^B G_{k1}^B\left(1-f_\infty^B\right)\right). \end{cases} \tag{12}$$

Furthermore, the final fractions S_∞^A and S_∞^B of nodes in the GCC can be expressed as

$$\begin{cases} S_\infty^A = p_\infty^A[1-G_{k0}^A(1-f_\infty^A)], \\ S_\infty^B = p_\infty^B[1-G_{k0}^B(1-f_\infty^B)]. \end{cases} \tag{13}$$

4. The symmetric case

We begin by assuming that both layers follow Poisson cardinality distributions, i.e., $e^{-\langle m\rangle}\langle m\rangle^m/m!$, which simplifies the analysis of Eqs. (11) and (12) that are typically solved numerically.

Consequently, we have

$$\begin{cases} G_{m0}^A(x) = G_{m1}^A(x), \\ G_{m0}^B(x) = G_{m1}^B(x). \end{cases} \tag{14}$$

From Eqs. (11) and (12), we derive

$$\begin{cases} f_\infty^A = T_\infty^A, \\ f_\infty^B = T_\infty^B. \end{cases} \tag{15}$$

This simplifies Eqs. (11) and (12) to

$$\begin{cases} f_\infty^A = 1-G_{m0}^A\left(1-p_\infty^A+p_\infty^A G_{k1}^A\left(1-f_\infty^A\right)\right), \\ f_\infty^B = 1-G_{m0}^B\left(1-p_\infty^B+p_\infty^B G_{k1}^B\left(1-f_\infty^B\right)\right). \end{cases} \tag{16}$$

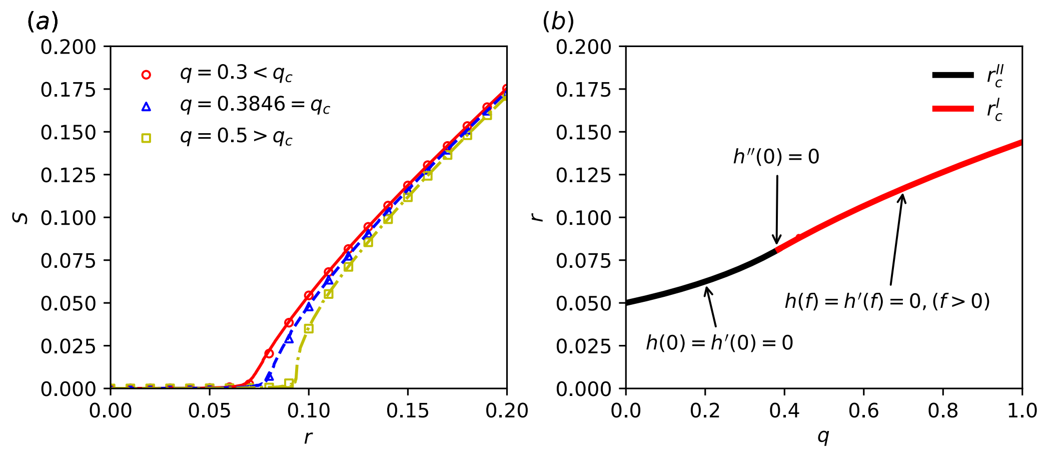

Fig. 2. The depiction of the collapse pattern within an interdependent hypergraph system is presented. The support degree, cardinality, and hyperdegree are each modeled through a Poisson distribution characterized by $\langle \tilde{k} \rangle = 4$, $\langle m \rangle = 5$, and $\langle k \rangle = 4$, respectively. (a) illustrates the fraction S of the GCC as a function of r for different values of q. (b) identifies the critical points corresponding to second-order and first-order phase transitions.

Moreover, if both hypergraph layers exhibit identical cardinality, hyperdegree, and support degree distributions, we obtain

$$\begin{cases} G_{m0}^A(x) = G_{m0}^B(x) = G_{m0}(x), \\ G_{k0}^A(x) = G_{k0}^B(x) = G_{k0}(x), \\ \tilde{G}_{k0}^A(x) = \tilde{G}_{k0}^B(x) = \tilde{G}_{k0}(x). \end{cases} \tag{17}$$

Assuming identical parameter settings, i.e., $q_A = q_B = q$, $r^A = r^B = r$, we find

$$f_\infty^A = f_\infty^B = f. \tag{18}$$

Thus, Eq. (16) simplifies to

$$f = 1 - G_{m0}\left(1 - r[1 - q\widetilde{G}_{k0}(1-f)][1 - G_{k1}(1-f)]\right). \tag{19}$$

Additionally, the size of GCC, $S_\infty^A = S_\infty^B = S$, is given by

$$S = r[1 - q\widetilde{G}_{k0}(1-f)][1 - G_{k0}(1-f)]. \tag{20}$$

To solve the critical point r_c^{II} for the second-order phase transition, i.e., a scenario where the order parameter S (the size of the GCC) changes continuously as a function of the control parameter r (the initial survival probability), we define

$$h(r,f) = 1 - G_{m0}(y(f)) - f, \tag{21}$$

with

$$y(f) = 1 - r[1 - q\widetilde{G}_{k0}(1-f)][1 - G_{k1}(1-f)]. \tag{22}$$

Since r_c^{II} satisfies $\partial_f h(r_c^{II}, 0) = 0$, we derive

$$G'_{m0}(y(0))y'(0) - 1 = 0, \tag{23}$$

with

$$\begin{cases} y(0) = 1, \\ y'(0) = G'_{k1}(1)(1-q). \end{cases} \tag{24}$$

Given that both layers follow Poisson cardinality and hyperdegree distributions, we obtain

$$r_c^{II} = \frac{1}{\langle m \rangle (1-q) \langle k \rangle}. \tag{25}$$

Furthermore, the fraction q of dependent nodes has a great impact on the collapse pattern of the system. As illustrated in Fig. 2, a pivotal transition in the system's collapse pattern is triggered as the value of q exceeds the critical point q_c. This transition, from a smooth, second-order phase transition to an abrupt, first-order phase transition, signifies a profound shift in the system's resilience.

Since at the critical point q_c, the condition for second-order and first-order phase transition are met, we must have the equation $\partial_f^2 h(r_c^{II}, 0) = 0$ which yields

$$G''_{m0}(y(0))(y'(0))^2 + G'_{m0}(y(0))y''(0) = 0, \tag{26}$$

with

$$\begin{cases} y(0) = 1, \\ y'(0) = -r_c^{II}(1-q_c)G'_{k1}(1), \\ y''(0) = -r_c^{II}\left(2q_c\tilde{G}'_{k0}(1)G'_{k1}(1) - (1-q_c)G''_{k1}(1)\right). \end{cases} \tag{27}$$

If hyperdegree and support degree also follow Poisson distributions for both layers, we can obtain

$$q_c = \frac{1}{1 + \frac{2\langle \tilde{k} \rangle}{\langle k \rangle + 1}}. \tag{28}$$

In Fig. 2(a), the curve labeled by $q = 0.3846 = q_c$, delineates the boundary between second-order and first-order phase transition. For $q = 0.3 < q_c$, the system undergoes a second-order phase transition at the critical point $r_c^{II} \approx 0.07143$ (verified by Fig. 3(a)). Conversely, when $q = 0.5 > q_c$, the collapse pattern of the system is an abrupt first-order phase transition at the critical point $r_c^I \approx 0.09553$ (verified by Fig. 3(b)).

Moreover, Eq. (28) reveals a profound relationship: the point q_c is inversely proportional to the average support degree $\langle \tilde{k} \rangle$ and directly proportional to the average hyperdegree $\langle k \rangle$. This relationship highlights a crucial principle: an augmentation in the density of support hyperedges within the system triggers a shift towards a lower transition threshold separating second-order from first-order phase transitions. Specifically, in Fig. 4, when $\langle \tilde{k} \rangle = 5$, $q = 0.4 < q_c$ results in the system undergoing a second-order phase transition.

However, as $\langle \tilde{k} \rangle$ increases to 10, $q = 0.4 > q_c$ occurs, causing the system to exhibit first-order phase transition. It is important to note that, a higher value of $\langle \tilde{k} \rangle$ makes the system more fragile, the potential for abrupt collapse necessitates vigilance.

5. Conclusion

Given the ubiquitous interdependence among diverse infrastructures, investigating cascading failures within interdependent systems is of critical importance. Our research endeavors to bridge a conspicuous gap in the existing literature by delving into cascading failures within interdependent hypergraphs with group support mechanisms. By integrating higher-order interactions and interdependencies between nodes

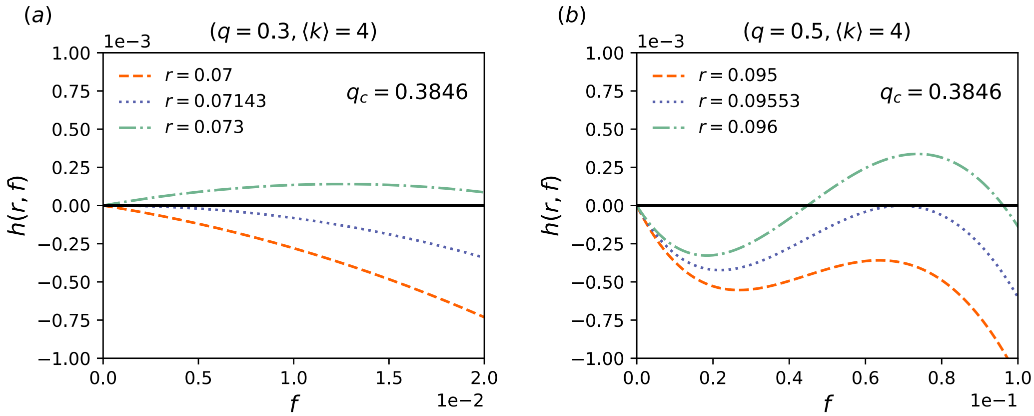

Fig. 3. Graphical solution of Eq. (21). The support degree and cardinality are modeled by a Poisson distribution with $\langle \tilde{k} \rangle = 4$ and $\langle m \rangle = 5$, respectively. The panels illustrate the scenario where the hyperdegree adheres to a Poisson distribution with $\langle k \rangle = 4$ for $q = 0.3 < q_c = 0.3846$ and $q = 0.5 > q_c = 0.3846$, respectively.

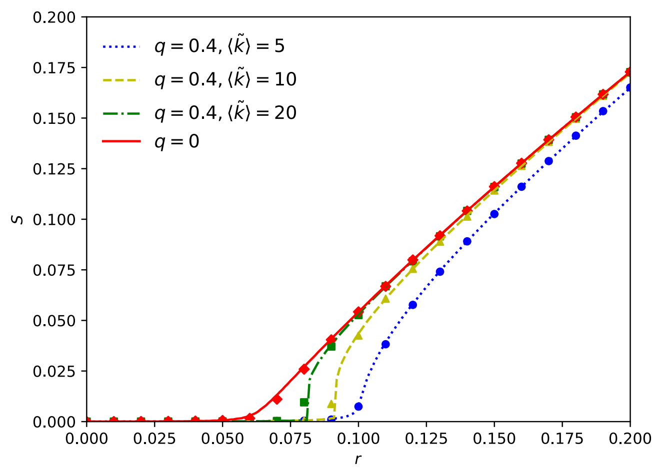

Fig. 4. The fraction S of GCC as a function of r for varying $\langle \tilde{k} \rangle$. The hyperdegree and cardinality are modeled by a Poisson distribution with $\langle k \rangle = 4$ and $\langle m \rangle = 4$, respectively. The lines denote theoretical predictions, while the points represent simulation results obtained with $N = 10^4$ nodes and $M = 10^4$ hyperedges.

and hyperedges across multiple layers, our model emerges as a robust framework for dissecting the intricate mechanisms that underpin the resilience of complex systems against cascading failures.

Our findings provide several profound insights into the resilience of interdependent hypergraph systems. We establish a critical threshold for the initial node survival probability, a boundary that demarcates the second-order phase transition within the system's dynamics. Furthermore, we deduce the critical fraction of dependent nodes, a pivotal indicator of the transition between second-order and first-order phase transitions. This critical point is intricately tied to the average support degree and the average hyperdegree, offering a nuanced understanding of system behavior.

Despite the valuable insights our model offers into cascading failures within interdependent hypergraphs, several avenues for future research remain uncharted. For instance, the introduction of intra-hyperedge dependencies could be explored, where the failure of a node might result in the collapse of the entire hyperedge it is embedded within. Additionally, our current model confines itself to two interdependent layers; extending this framework to multi-layer systems could unveil more complex patterns of failure propagation. Moreover, while our focus has been on the impact of hyperdegree and support degree distributions, other structural attributes, such as clustering coefficients and community structures, may also wield significant influence on the resilience of interdependent hypergraphs.

In summary, our research underscores the pivotal role of group support mechanisms and intricate network topologies in determining the resilience of interconnected systems against cascading failures. By constructing a double-layer interdependent hypergraph system, we have gained profound insights into how failures propagate across layers and culminate in system-wide collapses, which can offer valuable guidance for the design and resilience optimization of complex systems.

CRediT authorship contribution statement

Lei Chen: Methodology, Conceptualization, Writing – original draft, Software. **Juntao Lu:** Validation, Writing – original draft. **Yalin Wang:** Validation, Writing – original draft. **Chunxiao Jia:** Conceptualization, Supervision. **Run-Ran Liu:** Methodology, Conceptualization. **Fanyuan Meng:** Methodology, Conceptualization, Software, Writing – review & editing, Supervision, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

No data was used for the research described in the article.

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