A Tale of Two Cohesion: A Review of Group Cohesion in Social Psychology and Social Computing

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Abstract

Community detection and community search are two prominent social computing problems aimed at identifying cohesive groups, with wide-ranging social applications. In most studies, the precise quantification of *cohesion* is fundamental to the effective identification of communities. However, although the concept of cohesion originates in social psychology, its *structural dimensions* are the only aspects that have been formally captured through cohesiveness metrics. As a result, existing algorithms may be inadequate for addressing the nuanced requirements of community-driven social applications.

In this paper, we present a narrative review of cohesion definitions and measurement approaches across both social psychology and social computing, guided by our proposed unified framework. By examining the connections and disparities between these disciplines, we draw on insights from social psychology to inform the design of cohesiveness metrics that are psychologically meaningful. This review lays the groundwork for bridging these traditionally disparate fields, fostering interdisciplinary collaboration, and advancing the development of cohesiveness metrics capable of identifying communities that embody psychology-informed cohesion within online social networks.

1 Introduction

Community detection (CD) and *community search (CS)* are two interrelated problems that focus on uncovering communities, or subgraphs, in networks. Community detection generally analyzes the entire network to identify clusters or groupings of nodes [73], whereas community search is a query-driven approach that extracts a cohesive subgraph centered around a given query node or set of nodes [189]. Identifying and exploring communities in real-world networks is essential for understanding their structural organization and has broad applications across numerous domains [73, 85, 98, 103]. This paper undertakes a narrative review of community detection and community search algorithms in the context of online social networks, where they enable practical applications such as event planning, friend recommendation, and targeted marketing [65, 161]. These efforts significantly contribute to the broader domain of social computing [162, 203]. In the discussion that follows, the terms "social computing" and "community detection and community search" are used interchangeably.

In both CD and CS, communities are usually defined using quantitative criteria prior to extraction, and only subgraphs that satisfy these criteria are included in the results. *Cohesion* is generally accepted as an inherent property of such communities [65]. While there is no universally agreed-upon definition of a community, most approaches rely on metrics that evaluate the cohesiveness of nodes in a subgraph [65, 73, 74, 110, 146, 161, 167]. Recently, advancements in graph representation learning have led to a new line of research that identifies communities by learning cohesive patterns of communities directly from training data, eliminating the need for a predefined community definition [36, 37, 77, 191, 204, 207, 228].

1.1 A Tale of Two Cohesion

The concept of *cohesion* in social computing can be traced back to its origins in social psychology. Motivated by the need to understand groups and group processes, *cohesion*, also known as *group cohesion* or *cohesiveness*, was first proposed in social psychology to describe the invisible thread that weaves individuals into the fabric of a group [69]. Cohesion has been widely studied in various types of groups (e.g., sports [26, 166], military [159], and technology-mediated learning environments [224]) and has shown its critical role in shaping our social realities, influencing group performance, organizational functioning, and reported well-being [53, 72, 143]. To distinguish this concept from the one studied in social computing, we refer to it as *psychology-defined cohesion*.

Typically, the study of cohesion considers individuals or groups as units [208]. With the emergence of *social network analysis (SNA)*[1] and increasing awareness of the significance of studying interactions among social units, researchers began exploring network-based formalizations of group structures. Cohesion was subsequently regarded as a general characteristic of subgroup members and quantified through the strength of social ties within these groups. As a result, cohesive subgroups are formally defined by analyzing different properties of the ties among subsets of individuals [208]. With the emergence of CD and CS, the structural definitions of cohesive subgroups proposed in SNA, such as *k-clique*, *k-plex*, and *k-core* [113, 208], are adopted in defining communities [65, 73, 75, 208].

However, due to the shift of the focus on groups and cohesion from social psychology to social computing, the concept of cohesion may not be consistently or comprehensively characterized [229]. In social computing, cohesion is typically quantified using only network-based information [65, 73], often overlooking fundamental social psychological factors, such as the impact of social context on individuals' thoughts, perceptions, and behaviors, that are essential to a comprehensive understanding of group dynamics [41, 235]. This narrow focus on cohesion in community detection and search algorithms calls into question their suitability for real-world social applications, which require communities made up of individuals connected by diverse motivations and a genuine commitment to sustaining their membership. For instance, in digital marketing, core components of consumer communities include a sense of belonging, shared rituals and traditions, and a sense of obligation to the community and its members [192]. In the context of event organization, studies show that online communities constructed through discussions about shared values, norms, and community boundaries contain "virtual togetherness", which can be leveraged into political action [56, 114].

The toy example in Figure 1 illustrates how cohesion is studied from the perspectives of social psychology, social network analysis and social computing. Given the close relationship between community detection (CD) and community search (CS), as well as their common shortcomings in addressing cohesion from social psychology, we focus on CS for the sake of simplicity. In group cohesion studies, social psychologists typically study groups at the group level, as depicted in Figure 1(a), where eight users form a group. Their member-to-member and member-to-group relationships constitute a social context, indicated by the blue shading. Within the group, individuals interact with each other, with their thoughts, perceptions, and behaviors shaped by the social context. The degree of cohesion can be assessed by collecting individual responses using questionnaires such as the *Perceived Cohesion Scale (PCS)* (Table 1), and aggregating these responses to the group level by taking the average (e.g., $Mean = 3.46, SD = 0.59$).

When studying the same group from a network perspective, individuals are viewed as nodes, and their interpersonal connections are depicted as edges linking them [208]. In Figure 1(b), we present one possible social network studied by social network analysts, which can be constructed from individual-reported mutual friendship choices. By using k-core with $k = 3$ to identify a cohesive subgroup, where each node is connected to at least three others in the subgraph, the resulting 3-core consists of nodes

[1] Social network analysis is "an interdisciplinary field that developed out of a propitious meeting of social theory and application, with formal mathematical, statistical, and computing methodology" [208].

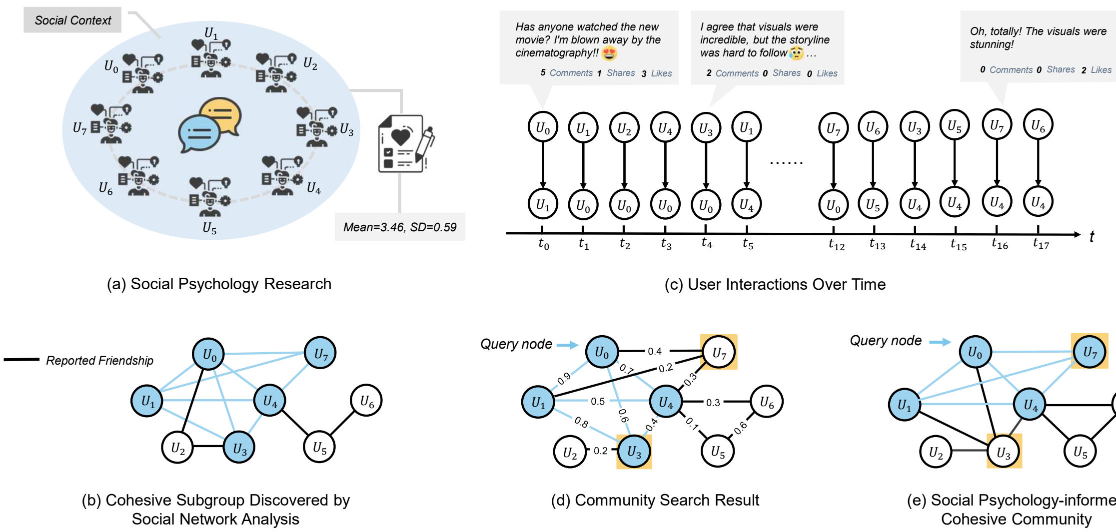

Figure 1: [Best viewed in color] Cohesion Studied in Social Psychology, Social Network Analysis, and Community Search.

Table 1: Perceived Cohesion Scale. Responses are recorded on Likert scales ranging from 0 ("strongly disagree") to 4 ("neutral") to 7 ("strongly agree"). The items are categorized into two groups, reflecting the sense of belonging (B) and feelings of morale (M), aligning with their adopted conceptual definition of cohesion.

Item
1. I feel that I belong to this group. (B-1)
2. I am happy to be part of this group. (M-1)
3. I see myself as part of this group. (B-2)
4. This group is one of the best anywhere. (M-2)
5. I feel that I am a member of this group. (B-3)
6. I am content to be part of this group. (M-3)

$\{U_0, U_1, U_3, U_4, U_7\}$. In this subgroup, every individual has at least three connections, indicating a tightly knit social unit.

Next, consider retrieving a community using user U_0 as the query node. Suppose the chronological interaction logs involving U_0 are available. As illustrated in Figure 1(c), each directed node pair represents a textual interaction sent from one user to another, either in the form of an initial post or a comment, expressing personal thoughts and feelings. In addition, user actions, such as likes and shares, indicate the extent to which posts resonate with other users. Figure 1(d) shows a network constructed from the interaction flow, where edge weights represent the interactiveness between user pairs, along with a community search solution [50, 63, 194]. Specifically, two cohesiveness metrics can be defined: a *structural-based cohesiveness metric* (k-core) and an *interactiveness cohesiveness metric*, operationalized by an *interactiveness score* that exceeds a user-defined threshold for each node pair. Using $k = 3$ and a threshold of 0.4, a subgroup $\{U_0, U_1, U_3, U_4\}$ can be identified (represented by blue nodes connected by blue weighted edges). However, although individuals in the subgroup engage with at least three others within the group and demonstrate relatively high interaction intensity, their perceptions of the group, as well as how their behaviors and attitudes are shaped by the broader social context, lack explicit and systematic characterization [66, 92]. As a result, interpreting the identified community as genuinely cohesive remains open to question. A closer look at the interactions in Figure 1(c) reveal that U_3's opinion towards the movie differs from others, including U_0. Despite receiving two comments, the post attracted no shares or likes. This lack of positive feedback may reduce U_3's willingness to engage further and affect the perception of belonging, potentially leading to his or her disconnection from the group. Consequently, a solution that includes U_3 may not necessarily be cohesive. Note that while such group dynamics are well studied in psychology-defined cohesion, no existing tools provide effective guidance for CS to identify such cohesive communities in online social networks [229].

1.2 Motivation and Overview of the Review

Based on the above observations, it is paramount that communities in online social networks should reflect cohesion as defined in social psychology. Therefore, community detection and search metrics ought to be designed to capture this form of cohesion. However, a recent experimental evaluation of representative community search algorithms on online social networks showed no clear correlation between structural and psychological cohesiveness, and none of the algorithms successfully identified communities that are psychologically cohesive [229]. Additionally, developing effective metrics to capture such cohesion faces several challenges. First, there is no comprehensive comparison between existing social computing metrics and psychology-defined cohesion. Second, no framework is available to guide the systematic development of effective cohesiveness metrics, despite extensive psychological research on measuring cohesion across various contexts and scopes.

To address the challenges in developing effective cohesiveness metrics, in this paper, we carry out a narrative review of the cohesion construct studied in social computing and social psychology, concentrating on its definition and measurement. We seek to shed light on the chasm between current cohesiveness metrics that social computing uses within online social networks and those adopted by social psychology, offering insights for more effective cohesiveness metric development. It is anticipated that integrating psychology-informed cohesiveness metrics into social computing algorithms would yield results that diverge from those of existing methods. For example, Figure 1(e) presents a possible psychology-driven community search result, where user U_3 is excluded and U_7 is included. According to social psychology, the inclusion can be explained by shared movie preferences and positive "likes" interactions between U_7 and other members, which reinforce social ties, cultivate a sense of belonging, and ultimately strengthen the overall cohesion of the community.

The rest of the paper is organized as follows: Section 2 reviews existing surveys about group cohesion in social psychology and social computing. Section 3 introduces the key terminologies used in our study. Section 4 illustrates the methodologies utilized for conducting the review. Sections 5 to Section 8 detail the group cohesion studied by both fields. Finally, Section 9 concludes the paper.

2 Related Work

This section briefly overviews surveys in social psychology, community detection, and community search, focusing on the definitions and measurement of cohesion. The differences between our work and existing studies are also highlighted.

2.1 Surveys in Social Psychology

In social psychology, cohesion is typically reviewed from a general perspective, focusing on its theoretical definitions and measurement issues [27, 48, 53, 55, 59, 96, 175], and its relationship to other constructs

[72, 130, 131, 143, 177]. Some studies also explore cohesion in specific contexts, such as sports [26, 166], the military [71, 159], and technology-mediated learning environments [224].

Previous studies have proposed several frameworks for reviewing cohesion. For example, Drescher et al. [55] applied multidimensional process classification system from [23] to identify key parameters for measuring cohesion across four dimensions: *Person* (the unit of observation and analysis), *Variable Function* (whether cohesion is treated as an antecedent or response variable), *Measurement Strategy* (information used to measure cohesion), and *Time* (whether time is held constant and how often the cohesion is measured). In [175], cohesion measurement is reviewed in the order of conceptualization, measurement dimensionality, operationalization, level of measurement, and level of analysis. The discussion also covers the temporal considerations, as well as logistical and practical issues related to data collection and analysis. This framework is further extended to include other research components that can help structure the cohesion studies, such as methods for studying group cohesion (i.e., obtrusive, unobtrusive, or mixed), data collection formats (i.e., surveys, log data, or both), and study types (i.e., longitudinal, cross-sectional, or design-based) [224].

Nevertheless, these surveys are limited to psychological works and do not involve the application of group cohesion concepts in other disciplines. Moreover, no standardized framework exists for reviewing cohesion definitions and measurements, which is crucial for comparing process variables across cohesion studies and integrating related findings. Our review proposes a unified framework built on advances in psychological research and applies it to analyze how cohesion is studied in both social psychology and social computing. This approach not only clarifies how cohesion is defined but also provides a step-by-step account of the development of its measurement.

2.2 Surveys in Community Detection and Community Search

Since 1955 [209], community detection (CD) has attracted sustained attention due to the prevalence of real-world communities and its practical applications, prompting a variety of surveys that summarize advancements in the field. Typically, these surveys summarize community definitions in existing papers, classify CD methods based on various criteria, and discuss their empirical validation and potential applications [7, 44, 73, 89, 98, 103, 146, 161, 167, 173, 191]. However, in these surveys, the term "cohesion" is either overlooked or narrowly defined in terms of dense structures, occasionally supplemented by high similarity [9, 19, 44, 76, 110, 146, 161, 167].

Only one survey reviews existing community search (CS) studies [65]. It systematically categorizes them based on the cohesiveness metrics they use (i.e., structural, and if considered, attribute-based), compares and analyzes these metrics, and assesses the corresponding methods on both simple and attributed graphs. However, its treatment of cohesion is highly field-specific, and it lacks a comprehensive evaluation of the effectiveness of these metrics.

To support social applications with more effective cohesiveness measures, our study sets itself apart from previous surveys by emphasizing the definition of cohesion and the development of related metrics in both social psychology and social computing. This perspective allows us to uncover limitations in the metrics currently used in social computing and to identify opportunities for their improvement.

3 Background

To set the groundwork for our review, this section introduces essential terminology from social psychology and graph theory, as well as techniques that consider cohesion to varying degrees.

3.1 Social Psychology Terminology

Concepts and Constructs. A *concept* is an idea expressed through symbols or words [14]. Concepts can vary in their level of abstraction, from precise and objective to highly abstract. A *construct* is an abstract concept developed to explain specific phenomena. In psychology, constructs, such as cohesion in our context, often reflect internal processes like thinking, feeling, or acting in specific ways, and cannot be directly observed or measured [183]. Although these two terms have distinct meanings, they are often used interchangeably in the literature [152]. Consequently, we do not differentiate between them in our paper.

Conceptualization. The process of transforming fuzzy and imprecise concepts into precise and concrete terms is known as *conceptualization* [14, 15]. In other words, conceptualization is a process of defining the study concept. The resulting construct is also termed as a "conceptual definition" or "theoretical definition", often simply called conceptualization [152, 183]. During the conceptualization process, constructs are characterized as *unidimensional* or *multidimensional*. A *unidimensional construct* has a single underlying dimension, while a *multidimensional construct* consists of two or more dimensions, each measured independently and subsequently combined to form the overall construct.

Operationalization. *Operationalization* is the process of formulating operational definitions after a theoretical construct has been clearly defined. These definitions, or measures, are concrete indicators or items that operate at the empirical level to measure the construct and imply procedures for collecting relevant data [14, 15, 51, 152]. Generally, there are three types of such measures: *self-report*, *behavioral*, and *physiological* [183, 184]. *Self-report* measures are those in which participants report their thoughts, feelings, and actions through interviews or questionnaires. *Behavioral* measures refer to the recording or observation of participants' behaviors, while *physiological* measures record participants' physiological processes, such as heart rate and facial muscle activity.

Reliability and validity. *Reliability* and *validity* are two general criteria for evaluating measures to ensure they consistently and accurately reflect the study construct. *Reliability* requires that the measured results can be replicated under identical or highly similar conditions [119]. Common methods for assessing it include *test-retest reliability*, *internal consistency reliability*, and *inter-rater reliability* (see Table 2 for definitions) [14, 183]. *Validity* reflects how accurately the measured social reality matches the study construct. It can be assessed theoretically and empirically [14]. Theoretical assessments evaluate how well a conceptual definition corresponds to its operational measures, including *face* and *content validity*. Empirical assessments, on the other hand, collect empirical data to evaluate measures from four aspects: *factorial validity*, *criterion validity*, *convergent validity*, and *discriminant validity* [14, 183]. *Criterion validity* can be further split into *predictive* and *concurrent validity*, depending on whether the studied measures and criterion are implemented simultaneously or asynchronously [119, 183]. *Convergent* and *discriminant validity* are often used together to assess related and pre-existing constructs [14]. These two types of validity are integral components of *factorial validity*, which is especially important for newly established constructs [78]. Table 3 summarizes the types of validity and their definitions. Ideally, measures should demonstrate both high reliability and validity. However, achieving consistent measurement results is often easier than ensuring accuracy, and these two criteria may sometimes conflict, necessitating a careful balance.

3.2 Graph Terminology

Next, we briefly introduce relevant graph terminology. For clarity of exposition, we illustrate the terminology on a small, simple, and undirected graph $G(V, E)$, with node set denoted as V and edge set as E, as depicted in Figure 2.

Table 2: Types of Reliability.

Reliability Type	Definition
Test-retest reliability	The degree of consistency between two assessment scores measuring the construct within the same sample at different time points.
Internal consistency reliability	The degree to which the rated items of the same constructs correlate with each other.
Inter-rater reliability	The degree to which two or more independent raters or observers agree on the same construct.

Table 3: Types of Validity.

Assessment Type	Validity Type	Definition
Theoretical	Face validity	The degree to which an indicator appears to reasonably measure its underlying construct.
	Content validity	The extent to which the full content of a definition is represented in a measure.
Empirical	Factorial validity	The extent to which the theoretical structure of a construct is reflected in the factor structure of a test or measure.
	Criterion validity	The extent to which measurement results correlate with an expected external variable (a.k.a. criterion). It includes two subtypes: predictive validity, when the criterion is measured after the construct, and concurrent validity, when the criterion is presumed to occur simultaneously with the construct.
	Convergent validity	The extent to which a measure aligns with other measures of the same or related constructs.
	Discriminant validity	The extent to which a measure discriminates from other constructs that are not expected to be measured.

k-clique. A clique is a complete subgraph that contains at least three nodes, where all nodes are adjacent to each other [134, 155]. A clique with k nodes is also called a *k-clique* [172]. In the graph displayed in Figure 2(a), the subgraph $\{U_2, U_3, U_4, U_5\}$ forms a 4-clique, with any three of its nodes form a 3-clique. $\{U_0, U_1, U_3\}$ is another example of a 3-clique. While the clique is a foundational idea for studying cohesive subgroups in social networks, its definition is often considered too strict: it overlooks node differences by imposing identical linkage requirements, making extracted subgraphs less informative. As a result, researchers have proposed different relaxations of the k-clique [208].

k-plex. One relaxation of the k-clique based on node degree is the *k-plex* [181]. A subgraph $S(V_S, E_S)$ is a *k-plex* if every node has at least $|V_S| - k$ neighbors within the subgraph [206]. A clique is a special case of a k-plex when $k = 1$, as illustrated in Figure 2(b), where the 1-plex (also a 4-clique) includes vertices $\{U_2, U_3, U_4, U_5\}$. Two additional 3-plexes are $\{U_0, U_1, U_2, U_3, U_6\}$ and $\{U_0, U_1, U_3, U_4, U_5\}$, where each node lacks no more than 2 internal connections.

k-core. The *k-core* is another relaxation of the k-clique based on node degree [180]. Let $deg_G(v)$ denotes the degree of a node v in G. A *k-core* is the largest induced subgraph $H \subseteq G$ where each node is adjacent to at least k nodes, i.e., $\forall v \in V_H, deg_H(v) \geq k$. In Figure 2(c), the largest 2-core subgraph consists of the nodes $\{U_0, U_1, U_2, U_3, U_4, U_5, U_6\}$, with each node connected to at least two other nodes. Within it, a denser 3-core, $\{U_2, U_3, U_4, U_5\}$, can be identified.

k-truss. The *k-truss* is also a relaxation of the k-clique, motivated by a natural observation of social cohesion: strongly tied actors may share connections with others [46]. It is defined as the largest subgraph of G in which every edge is contained in at least $(k-2)$ triangles [65]. For example, in Figure 2(d), a 3-truss includes nodes $\{U_0, U_1, U_2, U_3, U_4, U_5\}$, with each edge belongs to at least one triangle. When $k = 4$, a 4-truss can be found with nodes $\{U_2, U_3, U_4, U_5\}$.

k-ECC. A *k-edge-connected graph* (or *k-ECC*) belongs to a different genre of cohesive subgroup definition emphasizing edge connectivity [233]. For two vertices $u, v \in V$, the edge connectivity $\lambda(u, v)$ is the minimum number of edges whose removal disconnects u and v. A *k-ECC* is thus a connected subgraph

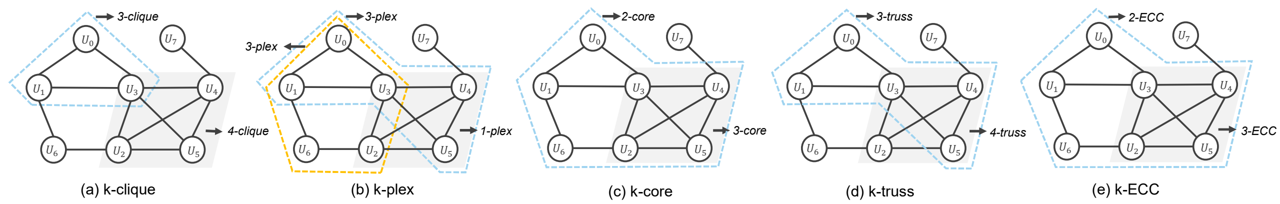

Figure 2: Cohesive Subgraphs in a Simple Graph.

that remains connected unless at least k edges are removed. As highlighted in grey in Figure 2(e), the subgraph of $\{U_2, U_3, U_4, U_5\}$ is 3-ECC, since at least three edges must be removed to disconnect it. The 2-ECC includes vertices $\{U_0, U_1, U_2, U_3, U_4, U_5, U_6\}$.

3.3 Social Network Analysis

Social network analysis (SNA), rooted in sociology and social psychology, is an interdisciplinary field that integrates social theory, formal mathematics, statistics, and computing methodologies [113, 208]. Unlike social psychology, which often treats social groups as unified entities, SNA focuses on social networks composed of individual actors and the relationships among them. Typically, relations between pairs of social actors have both form and content, depicting how information is exchanged to establish social reality [113]. The patterns of these relationships form network structures, which are described using structural variables to better understand both individuals and the group as a whole.

In SNA, one important task is to identify cohesive subgroups within a network, where cohesion is treated as a general property, quantified by the properties of social ties. Cohesive subgroups can thus be formalized by examining various tie properties among group members. As defined in [208], cohesive subgroups in social networks are *"subsets of actors connected by relatively strong, direct, intense, frequent, or positive ties"*. The formalization of a cohesive subgroup begins with a clique [68, 134], as discussed in Section 3.2. Due to its limited applicability for strict requirements [2], many alternative definitions have been proposed, including the *k-clique*, *reachability*, *diameter*, *n-clan*, *n-club*, k-plex, k-core, *LS Set*, and *Lambda Set* (see [208] for details).

It is worth noting that in SNA, network data, collected through questionnaires, interviews, and observations [113, 208], contains abundant social and psychological information. Questionnaires are especially common when studying human subjects, often including questions about their ties to other actors, involving questions such as whom they consider as close friends, feel confident about, or would like to seek advice from [4, 208]. However, self-reported social network data is susceptible to accuracy, validity, and reliability, as respondents may encounter challenges such as obtrusiveness, expansiveness bias[2], artificiality [11, 12, 141, 142]. These issues make it even more challenging to collect large-scale, long-term network data [11, 190].

3.4 Community Detection

The *community detection (CD)* problem stems from the recognition that real-world networks commonly exhibit underlying community structures with practical applications. It identifies communities, or clusters, within a graph by leveraging embedded network information [9, 44, 75, 76, 98, 161, 167]. Therefore, this problem is also referred to as graph/network clustering [73, 74].

Community detection is an ill-defined problem with no universal quantitative definition of object communities. The guiding principle behind most community definitions is that vertices within a subgraph

[2]The expansiveness bias is defined as the tendency to overreport and underreport one's interactions with others [67].

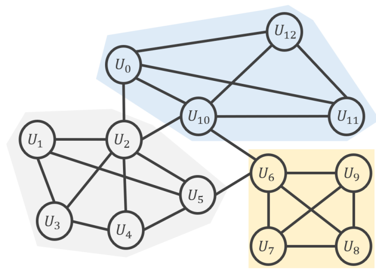

Figure 3: [Best viewed in color] Illustration of the Differences Between Community Detection and Community Search.

have more internal edges than links to the rest of the graph [73, 191]. Traditionally, target communities are defined based solely on graph topology and are classified as *local*, *global*, or based on *vertex similarity*. *Local* definitions, drawn directly from SNA, focus on subgraphs and the cohesion among internal vertices, disregarding the rest of the graph. *Global* definitions, on the other hand, concern the entire graph and assume that a community structure exists if the graph significantly differs from a random one. This can be verified by a *null model*, with *modularity* being the most popular one [153]. Lastly, communities can be identified based on the structural similarities shared by vertices (i.e., Euclidean distance, cosine similarity, Pearson correlation) [73, 161]. A simple example of traditional community detection is shown in Figure 3, where applying the k-core based algorithm with $k = 3$ partitions the network into three 3-core components, each highlighted in a different color.

However, traditional structure-based community definitions are argued by some to be insufficient to capture the forces for nodes to form communities, while incorporating node attributes alongside structural information from the real-world networks can result in more informative and robust community detection [44, 103]. Meanwhile, the results detected by algorithms designed with various metrics can also be regarded as communities, without the need for a predefined definition [73, 74, 186]. In recent years, recognizing that traditional methods struggle to capture the inherent features of target communities due to the lack of a unified definition, researchers have developed a series of learning-based approaches that identify communities directly from the network structure and attribute information, without requiring prior knowledge. This enables the discovery of more diverse communities [106, 191].

It is worth noting that, regardless of the methods used in community detection, communities are typically identified based on structural and, when available, attribute information. Few studies consider the concept of cohesion, and when they do, it is usually limited to structural density [40, 47, 91, 151, 210, 234].

3.5 Community Search

Community search (CS) is a query-dependent variant of the community detection problem, addressing the inefficiency of applying traditional CD methods to complex networks while offering enhanced customization capabilities [65]. First introduced in [189], CS aims to retrieve a cohesive subgraph from an input graph based on a query request, without traversing the entire graph. The original community search problem is formalized from a combinatorial optimization perspective as follows:

Problem 3.1: ***[Community Search (CS) Problem]*** Given an undirected graph $G = (V, E)$, a set of query nodes $Q \subseteq V$, and a goodness function f, the community search problem seeks to find an induced subgraph $H = (V_H, E_H)$ of G, such that

(i) V_H contains Q ($Q \subseteq V_H$);

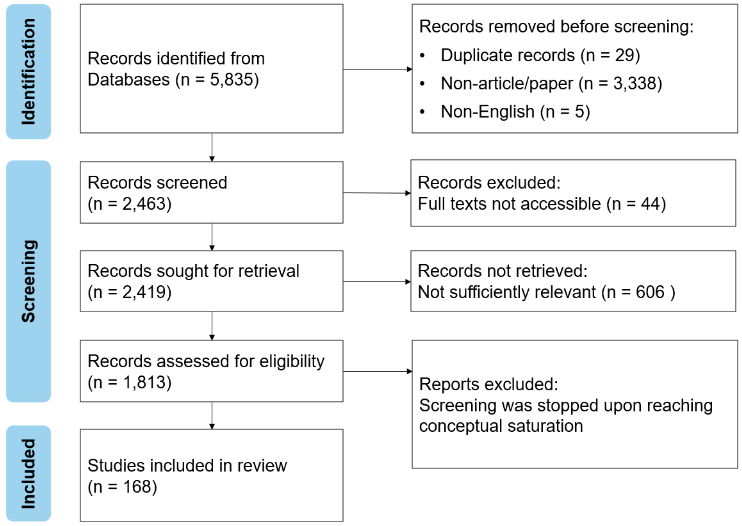

Figure 4: PRISMA Flow Diagram of the Study Selection Process.

(ii) H is connected;

(iii) $f(H)$ is maximized among all feasible choices for H.

In this formulation, the function f measures the goodness of the extracted community H, with larger values indicating denser internal connections [189]. The last two requirements are summarized subsequently in [65] as the *connectivity* and *cohesiveness* properties a community should satisfy. Common cohesiveness metrics in CS, namely k-core, k-truss, k-clique, and k-ECC, align with the cohesion formalization in SNA and local definitions of community in community detection. As shown in Figure 3, with query parameters set to $q = \{U_0\}$ and $k = 3$, a CS algorithm can retrieve a community consisting of vertices $\{U_0, U_{10}, U_{11}, U_{12}\}$, shaded in blue. Apart from structural cohesiveness metrics, *attribute-based* cohesiveness metrics have been developed to identify cohesive subgraphs by incorporating supplementary network information such as keywords, weights, profile, and temporality [65], as exemplified in Figure 1. In recent years, similar to community detection research, learning-based methods for community search have attracted increasing attention due to growing awareness of two key limitations in earlier approaches: structural inflexibility and attribute irrelevance. These models address these limitations by integrating both structural and attribute information into neural networks, eliminating the need for predefined patterns or rules [62, 77, 90, 105, 124, 204, 207].

4 Methodology

In this section, we first introduce the literature search and inclusion criteria for cohesion studies in social psychology, community detection, and community search, respectively. Then, we outline the review framework that guides the examination of selected studies.

4.1 Literature Search and Inclusion Criteria

In this paper, we adopted a narrative review methodology to provide a more selective survey of the literature on cohesion in both fields. This approach, as highlighted in [157, 163], is a great starting point to bridge related areas, stimulate theoretical development, and guide future research. Figure 4

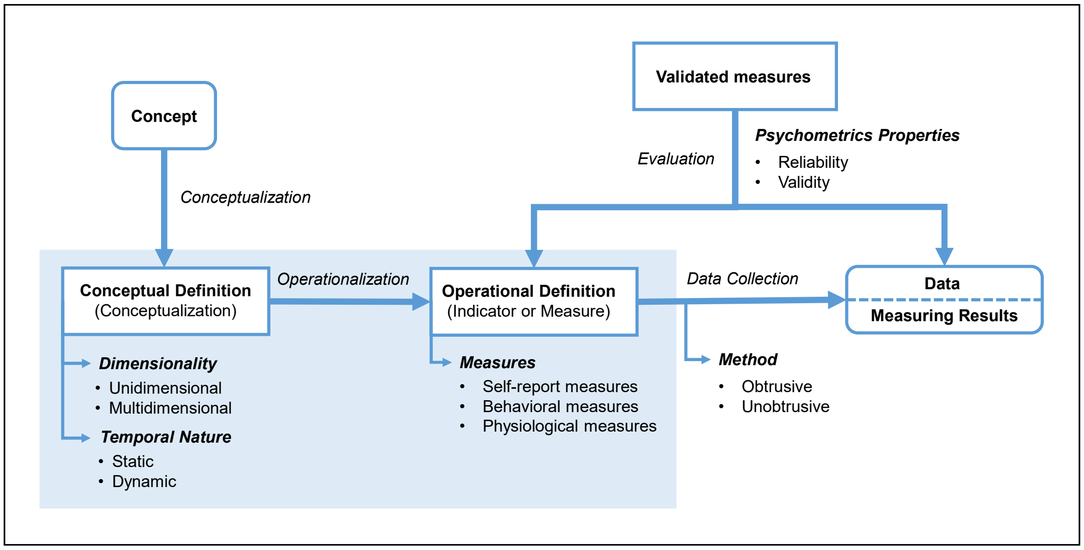

Figure 5: A Unified Framework for Reviewing Cohesion in Social Psychology and Social Computing.

presents the trajectory of the literature search and selection process, following the PRISMA guidelines [160]. To identify relevant studies on group cohesion, we used the search terms "cohesive", "cohesiveness", and "cohesion" in Google Scholar. For literature on community detection and community search, we retrieved studies from both Google Scholar and DBLP. The search terms for community detection were "community detection" and "detecting communities", while "community search" and "searching communities" were used for community search studies.

Before the screening procedure, three criteria were applied to the initially identified records: (a) duplicate papers were removed, (b) only journal articles or conference papers were retained, and (c) only English-language literature was included. The remaining records (n = 2,463) were screened based on full-text availability, and inaccessible articles were excluded.

For psychological studies, we included those that (a) adopted a concept of cohesion consistent with psychological definitions in their measurement approach and (b) measured cohesion directly. Social computing studies were included if their main focus was the development, evaluation, or review of community detection or search algorithms, rather than the application of such algorithms as tools for other tasks. Additionally, for survey papers on group cohesion and community detection/search, we applied snowballing techniques to include related studies that were not retrieved through our initial sources. This screening procedure yielded 1,813 papers eligible for inclusion in our study. The screening process was concluded once a clear understanding of research progress in both fields had been achieved. Focusing on representative rather than exhaustive coverage, we identified 168 relevant papers: 98 on group cohesion, 35 on community detection, and 35 on community search.

4.2 Review Framework

Following the thread that links group cohesion studies to social computing, as mentioned in Section 1, we propose a unified review framework to structurally examine the cohesion definitions and their measurement development across both fields, as shown in Figure 5.

The framework draws on the construct measurement processes from sociology and psychology research methods [15, 183], which begin with developing a conceptual definition of the construct, followed by operationalizing it into measures, implementing the measures, and finally evaluating them. To support the review, we also classify selected procedures and intermediate results, as has been frequently discussed

Table 4: Sampled Unidimensional Cohesion Conceptualizations with Keywords Highlighted.

Author	Conceptualization
Seashore [179, p. 97]	"... group cohesiveness was conceptualized as **attraction of members to the group** in terms of the strength of forces on the individual member to remain in the group and to resist leaving the group."
Lott [131, p. 408]	"Cohesiveness is defined as that group property which is inferred from the number and strength of **mutual positive attitudes among the members of a group**."
Cartwright [30, p. 91]	"The degree to which **the members of the group desire to remain in their group**."
Budman et al. [22, p. 202]	"Cohesion, according to the scale, is defined as **group connectedness**, demonstrated by working together toward a common therapeutic goal, constructive engagement around common themes, and openness to sharing personal material."
Forsyth [72, p. 219]	"Cohesion is just **a group's degree of unity**."

in existing surveys of psychological cohesion, into our framework [27, 53, 55, 71, 72, 83, 96, 143, 159, 166, 175, 177, 224].

Therefore, in our survey, we examine cohesion research by tracing how studies progress from conceptualization through operationalization to implementation and evaluation of these measures. Note that once the measures are established, they will be implemented to collect the data and, in some cases, to compute results. Measure evaluation may occur after its development, following data collection, or at both stages, depending on the specific methods used [15, 55, 152, 175, 183, 185, 224].

Note that although some psychology studies employ multiple research methods to investigate several variables, including cohesion, we only document the particulars concerning cohesion. For instance, in [97], self-reported data were collected to measure cohesion, while content analysis was used to assess groupthink; only the adoption of the obtrusive data collection is recorded in our survey. Moreover, it is necessary to clarify that our review framework, developed based on psychological research, does not fully align with the development of cohesiveness metrics in social computing due to their differing research perspectives. Specifically, unlike psychologists who study a construct by developing both conceptual and operational definitions, researchers in social computing directly propose formalized cohesiveness metrics or directly design learning-based models without an explicitly stated conceptual basis [65, 73, 106, 191, 208]. Therefore, we treated the definitions yielded from conceptualization and operationalization as a block to review, collectively referred to as "cohesion definitions" and marked them by a blue-shaded rectangle in Figure 5. To ensure alignment between the two domains, we manually extracted the conceptualizations of cohesion in social computing from the adopted cohesiveness metrics and separately examined how cohesion is addressed in learning-based models (see Section 6).

5 Cohesion Definitions in Social Psychology

In this section, we review group cohesion studies for their conceptual and operational definitions.

5.1 Conceptualizations

5.1.1 Cohesion Dimensionality

Cohesion conceptualizations can be categorized as unidimensional or multidimensional based on the number of dimensions used to define the construct. Despite extensive efforts to study cohesion since its inception [70], psychologists have yet to reach a consensus on its dimensionality [27, 48, 72, 175].

Sampled unidimensional cohesion conceptualizations are summarized in Table 4. Among these, the conceptualizations introduced in [179], [131], and [30] remain widely adopted in subsequent work [32, 87, 94, 202]. Unidimensional conceptualizations facilitate distinguishing cohesion from related concepts and are easy to operationalize [48, 143]. However, they may either be too ambiguous to capture the full complexity of cohesion or overly focus on a single factor, typically interpersonal attraction, at the expense of others [48, 59, 95, 96, 149, 200]. Besides, they are criticized for their limited applicability to certain group types [48]. For example, cohesion conceptualized in the therapeutic context as *"group connectedness, demonstrated by working together toward a common therapeutic goal, constructive engagement around common themes, and openness to sharing personal material"* [22], cannot be directly applied to educational or work groups without adaptation. Moreover, the inherently unidimensional nature of these constructs makes it difficult to compare them [48]. Consequently, most group cohesion studies have now embraced multidimensional conceptualizations.

Table 5: Sampled Multidimensional Cohesion Conceptualizations with Keywords of Each Dimension Highlighted.

Author	Conceptualization
Festinger [69, p. 7]	"Cohesiveness of a group is here defined as the resultant of all the forces acting on the members to remain in the group. These forces may depend on **the attractiveness or unattractiveness of either the prestige of the group, members in the group, or the activities in which the group engages**."
Carron [26, p. 213]	"... cohesion can be defined as a dynamic process which is reflected in **the tendency for a group to stick together** and **remain united in the pursuit of its goals and objectives**."
Zaccaro and Lowe [222, p. 838]	"... **interpersonal cohesiveness** represents the degree to which positive interpersonal relationships exist among members of the group. **Task-based cohesiveness** results when group membership provides for the personal attainment of important goals or when there is a 'shared commitment' to the task of the group."
Bollen and Hoyle [18, p. 482]	"Perceived cohesion encompasses **an individual's sense of belonging to a particular group** and **his or her feelings of morale associated with membership in the group**."
Bliese and Halverson [17, p. 1174]	"Vertical and horizontal cohesion are constructs reflecting the quality of relationships within groups. **Vertical cohesion** reflects subordinates' perceptions that leaders are considerate and competent. **Horizontal cohesion** is a measure of the degree of fraternal bonding and kinship within a group."
Griffith [84, p. 165]	"At the theoretical level, these cohesion scales hint at a two-dimensional concept of military-unit cohesion ...: **(a) the direction of cohesion**-contrasting vertical cohesion (referring to superior-subordinate relations) and horizontal cohesion (referring to peer relations); and **(b) the functions of cohesion**-contrasting instrumental cohesion (relating to task performance) and affective cohesion (relating to interpersonal support)."
Von Treuer et al. [200, p. 123]	"... cohesion was revealed to be a multidimensional construct made up of several elements... The elements were **(1) commitment to goal, (2) identify and respect, (3) interpersonal warmth, (4) belonging, (5) team success, and (6) proud of team identity**."

The multidimensional implication of cohesion can be traced back to its original 1950 definition, which stated that forces acting on members may depend on *"the attractiveness or unattractiveness of either the prestige of the group, members in the group, or the activities in which the group engages"* [69]. This multidimensional view has been widely adopted in subsequent studies, with some defining cohesion as bi-dimensional and others proposing three or more dimensions. A sample of these is listed in Table 5.

Commonly adopted bidimensional conceptualizations divide cohesion into task vs. social cohesion [26], belongingness vs. morale [18], and vertical vs. horizontal cohesion [17, 84]. Among these conceptualizations, the differentiation between task and social cohesion has gained widespread acceptance [13, 53, 60, 88, 107, 231, 232], where social cohesion assesses positive interrelationships among group members, while task cohesion captures the level of commitment of group members to achieving shared goals [26, 222].

An example of a multidimensional conceptualization is the six-dimensional model developed by Von Treuer et al. [200] using the *repertory grid technique* (RGT[3]) and *weighted multidimensional scaling*

[3]The RGT is "a form of structured interviewing, with ratings or without, which arrives at a precise description uncontaminated by the interviewer's viewpoint" [102]. It is used to determine the interrelations and structure of various cohesion dimensions [200].

(WMDS[4]). The six identified elements of cohesion are: (1) commitment to goals, (2) identification and respect, (3) interpersonal warmth, (4) belongingness, (5) pride in team success, and (6) pride in team identity.

Multidimensional models align more closely with existing knowledge on group cohesion and more effectively explain their relationship with response variables, such as decision-making, influence processes, and group dynamics [175]. However, as Cota et al. [48] noted, cohesion conceptualization can be affected by selecting either overly broad or excessively narrow items based on empirical criteria. This issue is further constrained by reliance on multivariate techniques such as factor analysis. Moreover, the growing number of proposed multidimensional models has not been matched by efforts to evaluate or compare them, making it challenging to identify the optimal models or integrate findings.

5.1.2 Temporal Nature

Time is a thread running through group processes to help understand how groups form, develop, and stabilize over time [5, 197]. We refer to this temporal aspect of conceptualization as the "temporal nature", which can be either static or dynamic, independent of its dimensionality. In general, cohesion is recognized as a dynamic construct that evolves as individuals interact, with perceptions of group cohesion becoming clearer [28, 117, 140, 175, 224]. This dynamism is further complicated by the varying contributions of multidimensional cohesion's components across different developmental phases, which may also differ among similar groups [27, 175]. Yet, most conceptualizations address this dynamic nature implicitly, only with one exception [26].

Given that cohesion is an emergent state[5] that evolves within groups [116, 140], our review reveals that most studies only collect data once, treating it inconsistently as a static construct. However, there is still a group of studies that emphasize its developmental aspect by examining how it changes across different stages of group development [21, 34, 57, 87, 136, 198, 224, 231]. For example, Lyles et al. [136] explored the longitudinal relationships between group cohesion dimensions and interaction variables (i.e., communication, cooperation, and competition) to inform strategies that promote physical activity within virtual communities.

5.2 Operational Definitions

Recall that operational definitions, also known as indicators or measures, precisely specify how cohesion is measured [14, 15, 119, 183]. The types of measures, including self-report measures, behavioral measures, and physiological measures [183, 184], may inform the methodologies used for subsequent data collection and how they vary in their effectiveness at capturing cohesion.

Among these three measures, researchers predominantly rely on self-report measures, particularly questionnaires, to quantify cohesion [14]. Question construction involves several stages, including determining the information needed and the way of administration, drafting questions, revising through multiple iterations, presenting, and final editing before being put into use [183]. Taking the development of the *Group Environment Questionnaire* (GEQ) [29], one of the most widely applied questionnaires, as an example. Based on the proposed conceptual model of group cohesion, the GEQ was constructed by first collecting the representative cohesion information related to it. This information was then used to develop items and ensure content validity. Next, the resulting questionnaire underwent a variety of item analytic procedures, ultimately yielding an 18-item instrument [29].

[4]WMDS is an exploratory statistical analysis used to generate the best-fitting model of the relationships between the elements, based on the similarity of their ratings [200].

[5]The term "emergent state" signifies "constructs that characterize properties of the team that are typically dynamic in nature and vary as a function of team context, inputs, processes, and outcomes". [140]

Behavioral measures of cohesion include externally rated scales and digital behavioral indicators, with the main challenge of their design being to fully and accurately describe studied behaviors. An example of the former is the *Group Cohesiveness Scale* (GCS) adopted in group therapy studies, where external raters assess cohesion by observing cohesive behaviors within the group [22]. The scale was developed through an iterative process of operationalization, including scale development, pilot testing by raters, and subsequent revisions. Consistent with the multidimensional nature of cohesion, the GCS includes five subscales: (a) Withdrawal and Self-Absorption vs. Interest and Involvement, (b) Mistrust vs. Trust, (c) Disruption vs. Cooperation, (d) Abusiveness vs. Expressed Caring, and (e) Unfocused vs. Focused, along with a global scale: Global Fragmentation vs. Global Cohesiveness. Practices using digital behavioral indicators are primarily found in online environments and are based on user-generated actions and content. For example, Altebarmakian and Alterman [3] connected participant behaviors with degree and manner of cohesion in the working groups and proposed three behavioral measures, namely behavioral engagement, interactivity, and cognitive engagement, to evaluate cohesion within working groups. In a study by Zamecnik et al. [225], temporal network motifs[6] that characterize the synchrony of team engagement are clustered to measure cohesion.

Self-report measures align well with the nature of cohesion, which is primarily rooted in individuals' perceptions of group members [118], despite their potential inaccuracies due to the individuals' subjectivity, including self-deception and memory biases [165]. However, given the dynamic nature of cohesion and the availability of longitudinal human interaction data, behavioral measures warrant further exploration. Evidence demonstrates that individual behaviors and social interactions captured by wearable social sensors can predict self-reported cohesion in longitudinal missions [227]. Meanwhile, direct physiological measures are notably absent [3], with only preliminary efforts showing that physiological synchrony, such as the interbeat intervals (IBIs) of the heart [82, 196] and smiling [147], can predict self-reported cohesion.

While neither self-report nor behavioral measures are ideal for capturing cohesion, combining both can help offset their individual limitations. Especially, well-developed self-report measures should be supplemented by behavioral ones [116]. For instance, Prewett [168] used both approaches to quantify cohesion and examine its relationship with performance. Their findings revealed strong consistency between self and observer ratings, both of which significantly predicted team errors and backup behaviors.

6 Cohesion Definitions in Social Computing

In this section, we review the study of cohesion in social computing, compare it with psychological research, and analyze insights for designing cohesiveness metrics. We start with the conceptual definitions manually extracted from existing studies, followed by their operational definitions. Next, we examine how learning-based methods address cohesion. Lastly, we outline two additional social computing techniques used to measure cohesion.

6.1 Conceptualizations

Unlike social psychology research, which formally proposes or adopts cohesion conceptualizations, community detection/search studies directly incorporate the understanding of cohesion into quantifiable metrics to characterize target communities, lacking explicit definitions. To identify the gaps and connections of cohesion between the two fields, we manually extract the cohesion conceptualizations

[6]Network motifs refer to statistically significant repeating structures within a larger network that characterize its composition [145].

Table 6: Extracted Cohesion Conceptualizations in Community Detection Studies.

Dimensionality	**Temporal Nature**	**Extracted Conceptualization**	**Work**
Unidimensional	Static	Vertices have more internal connections than links to the outside.	[40, 151, 187, 210, 213, 217, 234]
		Each edge belongs to at least k-2 triangles inside the subgraph.	[47]
Multidimensional	Static	Nodes with both similar semantic context and close internal relationships.	[221]
		Nodes with both high degrees of structural and content similarities.	[100]
	Dynamic	A core of people that remain in them over different time periods.	[42]
		People influence each other over time and eventually converge due to the presence of a "unity of will" or "sharing common values".	[182]

from existing cohesiveness metrics in community detection and search research, and categorize them using our review framework, as outlined in Tables 6 and 7, respectively.

In social computing, the categorization of cohesion conceptualizations depends on the number of aspects considered to characterize communities. Typically, unidimensional cohesion is defined structurally by the density of connections among nodes, the distance between nodes, the fraction of neighbors, or the count of triangles, as listed in Table 6 and 7. In contrast, psychological definitions focus on the individual perceptions of the group as a whole or regard cohesion as an intrinsic property of the group. They define cohesion as the individual's attraction to the group, group connectedness, or the group's unity, as illustrated in Table 4.

This comparison reveals that the focus and scope of cohesion conceptualizations differ between social psychology and social computing. Structural features emphasized in community detection and search research are either neglected or not explicitly addressed in cohesion studies. This difference can also be observed in Figures 1(a) and 1(d), where the network structure is especially highlighted in the latter. It is worth noting that although unidimensional psychological definitions of cohesion have been criticized for their ambiguity [48, 96], they convey richer social meanings than structural characteristics.

In multidimensional conceptualizations, both community detection and community search studies use an additive approach to define cohesiveness, which enhances the homogeneity of identified communities by integrating diverse information. Specifically, studies begin with structural cohesion and incorporate additional information, such as keywords, types, followerships, time, and global structural information into the characterization of cohesion. For example, the two-dimensional conceptualization defined in [63] requires nodes to have keyword cohesiveness in addition to structural cohesiveness, involving both structural and node information (see Table 7). In particular, community detection studies such as [42] and [182] explicitly reference the sociological origins of the cohesion concept, with the latter defining cohesion through "unity of will" and "sharing common values", closely aligning with the psychological definitions (see Table 6).

However, this common additive transition from unidimensional to multidimensional cohesion differs from group cohesion research in psychology, where the general concept of cohesion is decomposed into distinct, concrete dimensions. Despite providing a richer informational context than unidimensional models, multidimensional conceptualizations in social computing still fall short of capturing the full depth of social psychological cohesion. For example, while structural and keyword cohesiveness developed in [63] may contribute to the aforementioned interpersonal and task-based cohesiveness, they do not explicitly characterize psychological elements such as positive relationships and shared commitments, especially in the absence of data such as the content and temporal aspects of members' interactions.

When the temporal aspect is considered in social computing, time is explicitly reflected in cohesiveness metrics [40, 42, 50]. Meanwhile, since temporal cohesion builds on structural cohesion, these studies

Table 7: Extracted Cohesion Conceptualizations in Community Search Studies.

Dimensionality	Temporal Nature	Extracted Conceptualization	Work
Unidimensional	Static	Vertices are densely connected in the subgraph.	[8, 10, 38, 122, 125, 126, 129, 144, 189]
		The distance of any two nodes in the subgraph is not longer than a specific number of hops.	[123]
		Two groups, in which group members are densely connected and have a required number of butterflies, have dense cross-group interactions.	[54]
		Size-bounded vertices are densely connected in the subgraph.	[218]
		The number of nodes that need to be removed to disconnect the subgraph.	[101]
		Each vertex has at least k neighbors and at least p fraction of its neighbors in the maximal connected subgraph.	[133]
		Edges in a maximal subgraph can connect through a series of edge-adjacent triangles, with each edge present in at least k-2 triangles.	[215]
		Vertices are densely connected under multi-faceted relationships in the subgraph.	[36]
Multidimensional	Static	Structural cohesiveness: vertices are densely connected in the subgraph; Keyword cohesiveness: vertices share common keywords in the subgraph.	[63]
		Structural cohesiveness: vertices are densely connected in the subgraph; Spatial cohesiveness: vertices are spatially close to each other in the subgraph.	[39, 64]
		Structural cohesiveness: vertices have close relationships in the subgraph; Type cohesiveness: vertices are in the same type in the subgraph.	[104]
		Local cohesiveness: vertices are densely connected in individual layers; Global cohesiveness: vertices are densely connected in the projected graph.	[135]
	Dynamic	Structural cohesiveness: vertices are densely connected in the subgraph; Query cohesiveness: vertices are temporally similar in terms of their activities related to the query attributes in the subgraph.	[50]

inherently treat cohesion as multidimensional. However, not all social computing studies address the dynamic nature of cohesion, similar to the case in psychological studies. Hence, we advocate that the time dimension of cohesion needs further emphasis.

Based on our discussion, social computing would benefit from adopting cohesiveness metrics designed with guidance from widely accepted multidimensional and dynamic cohesion conceptualizations in social psychology. A recent study [229] takes a step towards this direction.

6.2 Operational Definitions

In social computing, cohesion is often mathematically formulated as cohesiveness metrics, utilizing structural and, when available, attribute information (see surveys mentioned in Section 2.2). However, these metrics are abstract and lack sufficient context-related information [65, 76]. Even Shao et al. [182], who recognized community as a tight and cohesive social entity, still detected communities using purely structural measures: network centrality, hierarchical cluster analysis, and similarity across different time points. Social psychology measures, by contrast, enable a more subtle characterization of cohesion by considering the thoughts, feelings, or behaviors of individuals within a group [15, 119, 183].

The varying level of detail in operational definitions between fields also affects how existing measures are applied to different research objects. In social psychology, existing measures, especially self-report measures, often require adaptation to fit new contexts, thus enabling participants to express their perceptions effectively [25, 34, 43, 45, 52, 132, 137, 195, 199, 214, 230]. For instance, Carless and De Paola [25] and Blanchard et al. [16] adapted the Group Environment Questionnaire (GEQ), originally designed for sports groups, for use in work and exercise groups by changing the item wording. Similarly, the Perceived Cohesion Scale (PCS), initially developed for large groups, was adapted by Chin et al. [43] for smaller group contexts. In social computing, however, the abstract nature of cohesiveness metrics allows their unadjusted application across social networks, which hinders their ability to measure psychological cohesion in specific contexts accurately. For instance, [182] applied generic measures across various networks–including non-human ones–despite the diversity of human contexts (e.g., clubs, college football teams) where cohesion may be conceptualized differently by participants. Similarly, in our running example (Figure 1(d)), using unmodified structural and interactiveness metrics–originally designed for the interaction network in Figure 1(c)–on a collaboration network may overlook shared task commitments, a key aspect of cohesiveness in collaborative settings.

Considering the concrete networks where the algorithms are applied, cohesiveness metrics can also be classified as either self-report or behavioral, similar to cohesion studies. For example, when the structural cohesiveness metric is applied to the "who-trusts-whom" network, where members report trusted relationships, it functions similarly to a self-report measure [233]. The metrics serve as behavioral measures when algorithms like *attributed community query* (ACQ) are applied to real-world online social networks where vertices are humans and edges represent behaviors such as following, commenting, or co-authoring [63]. In contrast to social psychology, which relies heavily on self-report measures, behavioral measures are widely adopted in social computing. This difference can be attributed to its focus and target applications on large-scale networks, which are typically built based on digital traces of users rather than self-reports [65, 148, 167, 173].

To develop more effective cohesiveness metrics grounded in psychological cohesion definitions, researchers can refer to social psychology measures, which offer concrete measurement actions based on clear conceptualizations. Metric formulation should incorporate context-specific information from target networks. Besides, when applying metrics to different networks, necessary adjustments should be made to ensure their suitability. Returning to the example in Figure 1, to search for a psychology-informed cohesive community, cohesiveness metrics could be formalized based on a specific cohesion conceptualization while incorporating the available network information, such as interaction content, timestamps, and user profiles. The scope of measures should be clearly stated, e.g., limited to online social networks with similar data, to imply the necessity of adaptation when they are applied in different contexts.

6.3 Cohesion Definitions in Learning-based Social Computing

Most learning-based community detection research neglects the concept of cohesion [170, 211, 212, 228]. When cohesion is mentioned, it typically appears only as a superficial goal, identifying node clusters with high cohesiveness, without deeper conceptual and operational engagement [91]. In contrast, learning-based community search studies show greater awareness of the cohesion concept. However, cohesion remains narrowly conceptualized, with models primarily targeting network features like community structure and, occasionally, attribute homogeneity [36, 61, 62, 77, 105, 124, 204, 205, 207]. Even when temporal factors are incorporated, as in [90], where a *Temporal Graph Convolutional Network* (CS-TGN) is designed to capture node attributes, structural properties, and their dynamics across network snapshots, only the structural aspect of networks is linked to the cohesion concept.

6.4 Other Techniques Designing Cohesion Measures in Social Computing

Given the significance of psychological cohesion, multiple approaches have been proposed in social computing to quantify it directly or indirectly from perspectives beyond the traditional psychological framework. Here, we briefly review two such techniques: *linguistic style matching* and *supervised learning*.

Linguistic style matching (LSM). Originating from linguistic research, *linguistic style matching* quantifies the degree of stylistic similarities in language use across individuals and groups [154]. Gonzales et al. [81] found that individual cohesion can be automatically predicted by evaluating the verbal mimicry of function words using LSM, with consistent accuracy regardless of the communication settings. However, subsequent studies have raised concerns about its generalizability. In global group collaboration, Castro-Hernández et al. [33] revealed that the LSM's correlation with task cohesion is weaker than that of *information exchange similarity*, a straightforward word-based calculation method. In asynchronous communication online, Munson et al. [150] found no support for LSM in predicting group cohesion, noting that its effectiveness may be influenced by individual participation levels and multilingual text features.

Supervised learning. In recent decades, studies have begun to develop cohesion measurements using computational techniques, including Support Vector Machines (SVM), Naive Bayes Classifier, Random Forest Classifier, and deep supervised networks. These supervised learning methods are trained on labeled data to predict cohesion levels, often leveraging multimodal communication cues such as text, audio, images, video, and motion [31, 178]. In [99], nonverbal cues (i.e., audio, visual, and audio-visual cues) were automatically extracted either on the individual or group level. SVM and Naive Bayes classifiers were then used to estimate whether a meeting had high or low cohesion. To evaluate these methods, cohesion annotations were collected from external observers using questionnaires based on psychological literature. In [79, 86], multi-task convolutional neural networks were trained for cohesion estimation, using face, body, and contextual cues extracted from images with supervision based on annotator-labeled cohesion. Besides, Walocha et al. [201] used a Random Forest Classifier to jointly predict the dynamics of social and task cohesion through large-scale spatial and bodily movement features, where labels are cohesion scores collected from the Group Environment Questionnaire (GEQ) instead of third-party annotations. The model achieved an average prediction accuracy of 64% (±3%) for task cohesion and 67% (±3%) for social cohesion [201].

Although supervised learning has shown its potential for automating cohesion measurement, it is still in the early stages with several limitations to be addressed. First, the extraction of communication cues and the establishment of cohesion measures, despite their basis in psychology, lack robust integration with cohesion studied in psychological research. Second, it can be expected that accurate automated cohesion scoring relies heavily on high-quality labeled datasets. Ideally, labels should be annotated via results from well-established psychological measures. However, the current labels in the datasets are often assigned by external observers through labor-intensive processes, and their relationship with psychological cohesion remains unclear.

7 Data Collection

Data collection methods for measuring cohesion are closely tied to how cohesion is operationalized [15]. In this section, we exclusively review the data collection methods adopted in group cohesion studies, categorized as *obtrusive* or *unobtrusive* (as detailed in Table 8). Thereafter, we review the data collection practices in social computing and discuss how they can be refined by incorporating insights from psychological studies.

Table 8: Data Collection Methods.

Type	**Method**
Obtrusive	Survey research Structured observation
Unobtrusive	Digital trace data collection methods

7.1 Obtrusive Methods

Obtrusive data collection methods explicitly inform participants that they are being studied [93]. Two such methods are commonly used in cohesion studies: *survey research* and *structured observation*, with surveys being more common. Survey research uses self-report measures, specifically questionnaires, to collect responses from well-defined populations. Structured observation, an observational method involving researcher intervention, creates a context in which participant behaviors can be more easily and quantitatively recorded by applying behavioral measures in laboratory or natural settings [183]. In the study by Budman et al. [22] (see Section 5.2), structured observation involved reviewing videotapes from time-limited group therapy sessions, during which two experienced raters observed cohesive behaviors within the groups and then assessed them using the GCS. In research adopting both self-report and behavioral measures [168], both survey research and structured observation are correspondingly employed in data collection.

Both obtrusive methods rely on differing interactions between researchers and respondents to gather extensive information from individuals. However, they are susceptible to distinct biases, such as response style bias in surveys and rater bias in structured observation [6, 225]. Besides, both can be labor-intensive, especially when studying the dynamic nature of cohesion over time or studying large groups [175]. These limitations urge the need for developing low-cost, unobtrusive data collection methods.

7.2 Unobtrusive Methods

Unobtrusive data collection methods allow subjects to be studied without awareness, making them well-suited for continuous or near-continuous assessment [6, 115]. In traditional psychology research, non-reactive data sources include physical traces, mass media, archives, etc. In recent years, as technologies increasingly mediate and support human activities, individuals' behaviors, as well as their intentions and emotions they reflect, can be inferred from digital traces recorded on digital systems, such as business transaction systems, social media platforms, and sensors [111, 158, 171]. These vast and continuously generated digital traces in online settings offer researchers new opportunities to study team processes and social phenomena [111, 115]. We term various approaches used for gathering digital traces as "digital trace data collection methods", which can be either obtrusive or unobtrusive. Obtrusive methods involve making video calls or accessing personal emails, while unobtrusive methods include application programming interfaces (APIs), data donation, tracking, etc [111, 158, 171, 175].

Based on our review, the digital trace data collection method serves as the primary method for gathering unobtrusive data in cohesion studies. For example, Altebarmakian and Alterman [3] unobtrusively collected students' data via an online system throughout a semester. Similarly, Zamecnik et al. [225] gathered three weeks of engagement data from a global experiential learning platform, involving 420 teams from various higher education institutions. Collecting digital traces overcomes the inherent limitations of obtrusive methods by enabling efficient, cost-effective data collection over time. It can capture the long-term dynamics of cohesion and offer greater flexibility in participant selection, unconstrained by geography or group size [6, 174]. Furthermore, the resulting datasets may be reused and support the application of various cohesion measures [171], making this approach promising for broader adoption.

However, this method also has limitations. First, it is not suitable for groups that require in-person participation, such as sports and exercise groups. Second, since the digital traces are generally not generated for research purposes, they are susceptible to misinformation, coverage error[7], and over-interpretation. As such, the data must be carefully cleaned and interpreted before being used for

[7] Coverage error refers to the selective representation of the platform user population compared to the general population [158].

measurement [6, 15, 111, 158, 171, 177, 185].

Therefore, using both obtrusive and unobtrusive data collection methods together is seen as a way to balance their respective limitations. Some researchers suggest using digital trace methods to complement traditional approaches, obtaining more diverse, extensive, and potentially less biased data [6, 171]. There is also an inspiring attempt to construct a multi-modal dataset utilizing both types of methods [139]. The dataset not only contains sound, video, and motion capture data collected from participants engaged in an 11-hour escape game, but also includes ongoing self-reported cohesion data collected through questionnaires.

7.3 Discussion

By tracing the original studies behind commonly used social network datasets in social computing and extracting their data collection details, we find that most datasets used in social computing are digital traces collected from online platforms, such as *Facebook*, *X* (previously *Twitter*), *YouTube*, *Flickr*, *Live Journal*, *Myspace*, and *Tencent* [8, 39, 50, 54, 63, 100, 123, 128, 133, 169, 210, 217]. Only a few datasets, particularly those used in community detection, are gathered through survey research, structured observations, or digitalized records of face-to-face interactions. For example, the Zachary karate club network was built using data from direct observation, informants, and club records in the university archives [223]. The "Jazz musicians" dataset is constructed from the collaboration data stored in the Red Hot Jazz Archive digital database [80]. Sometimes, network datasets are collected along with "ground-truth" communities [216], which are instrumental in validating social computing algorithms by comparing their outputs to known community structures. However, the definitions of these communities vary, and psychological cohesion is rarely, if ever, explicitly referenced [112, 121, 138, 216, 219].

The preference for digital trace collection in social computing contrasts with group cohesion studies, where survey research is commonly used. Besides, the two fields differ in their attention to the data collection process. Psychological studies typically collect data firsthand, providing detailed descriptions of participants and procedures. In contrast, social computing often relies on existing datasets, focusing more on algorithm design and performance than on data collection. As a result, dataset details are frequently overlooked, and only a few studies collect their own data [42, 128].

Based on the above observation, it can be inferred that network datasets built on digital traces share the same limitations identified in psychological studies. Concerning the general reliance of social computing on digital traces, it is important to maximize their advantages. Informed by existing endeavors in social psychology, researchers should carefully clean and interpret the digital traces. Besides, survey research can serve as a complementary method to validate the quality of the digital traces. Social computing could also benefit from datasets containing valid ground-truth communities that align with psychologically defined cohesion [229].

8 Evaluation

In psychological studies, the quality of a measure is evaluated through its reliability and validity, with the timing of these evaluations varying by method: some are conducted theoretically once the measure is established, others are empirically implemented following data collection, or at both stages [14, 119, 183]. In this section, we review how cohesion studies evaluate their measures. Then we compare those approaches with the evaluation of cohesiveness metrics in social computing, exploring insights that may guide the evaluation of cohesiveness metrics.

8.1 Reliability

Reliable measures seek the consistent and stable measuring of construct and are evaluated after data collection [14, 119, 183]. Three common types of reliability are test-retest, internal consistency, and inter-rater reliability (for definitions, see Section 3.1). The choice of method depends on the construct's temporal nature and the adopted operational definition.

In cohesion studies, internal consistency, often measured using *Cronbach's alpha*, is commonly evaluated due to its simplicity and direct relevance to questionnaires [14, 49]. It averages all possible split-half correlations for a set of items [49]. In our review, reported Cronbach's alpha for cohesion measures ranged from 0.542 to 0.991, with most exceeding the 0.70 threshold, indicating good internal consistency [156, 193]. In addition, test-retest reliability, which presents the stability of cohesion measurements over time, is validated by correlating the scores of samples collected at different intervals [16, 34]. When behavioral measures are used, inter-rater reliability ensures cohesion is consistently quantified across different observers [14, 120].

Ensuring measurement reliability is critical but often challenging. Common sources of unreliability include observers' subjectivity, and questions that are imprecise, ambiguous, or unfamiliar to respondents [14]. Strategies to improve reliability include clearly conceptualizing constructs, utilizing precise measurement levels and multiple indicators, and conducting pilot tests [25, 29, 34, 58, 119, 120].

8.2 Validity

A measure with high validity guarantees a strong alignment between the cohesion conceptualization and its empirical measurement results. Validity can be assessed from both theoretical and empirical perspectives.

Theoretical validity includes face and content validity, typically conducted by expert panels to ensure that measures adequately represent the cohesion definition [14, 60]. For instance, in developing the *Youth Sport Environment Questionnaire* [60], 142 initial items were evaluated by investigators for relevance, similarity, and clarity. These items were then refined based on feedback from additional group dynamics experts and athletes, resulting in 87 items.

Empirical validity is assessed using participant data. Factorial validity is often evaluated via pilot testing to ensure the measure reflects the underlying construct structure of cohesion. A practice of this assessment is detailed in [16]. While some studies only evaluate convergent or discriminant validity [35, 188, 220], it is more common to assess both simultaneously [24, 25, 52, 87, 108, 109, 118, 164, 176, 202, 230]. Empirical validity can also be substantiated through correlation with criteria expected to be associated with cohesion [183]. Concurrent validity is established when a measure correlates significantly with a criterion assessed concurrently. For instance, Estabrooks and Carron [58] examined the concurrent validity of the *Physical Activity Group Environment Questionnaire* (PAGEQ) by correlating it with the Group Environment Questionnaire (GEQ). Predictive validity assesses the correlations between cohesion and its expected future outcomes, such as attendance [58, 120], self-efficacy [58], individual perceptions of job performance, job satisfaction, and psychological distress [1].

Ideally, a thorough validity assessment should integrate both theoretical and empirical approaches. However, while newly developed cohesion measures typically undergo comprehensive validity assessment, adapted measures for different contexts or populations may not receive the same level of scrutiny, as noted in several studies [16, 25, 58, 60, 176]. For instance, when a questionnaire originally designed for student teams was adapted for serious game teams, only face and content validity were assessed, with other empirical evaluation neglected [20]. This limited approach can yield unreliable responses that misalign with the adopted cohesion conceptualization. More holistic evaluation of adapted measures is therefore essential to ensure their appropriateness for specific contexts and populations.

Table 9: Similarities and Differences in Cohesion between Social Psychology and Social Computing.

Components	**Aspects**	**Similarities**	**Differences**	**Social Psychology**	**Social Computing**
Conceptual Definitions	Dimension	Both can be classified as either unidimensional or multidimensional	Focus and scope	Neglect or implicitly address the structural features of cohesion, yet contain sufficient psychological meanings	Emphasize structural and attribute features of cohesion with insufficient psychological consideration
			Relationship between unidimensional and multidimensional definitions	From ambiguous to concrete and empirical	From solely structural to additive inclusion of non-structural aspects
	Temporal Nature	The dynamic nature is frequently overlooked	Treatment of the dynamic nature	Dynamic nature does not impact conceptual dimensionality	Incorporate dynamic nature as an additional dimension in definitions
Operational Definitions	Measures	Both adopt self-report and behavioral measures	Measurement concreteness	Include concrete measurement procedures	Mathematically formulated, need the specification or pre-calculation of parameters
			Approaches for applying existing measures to different study objects	Measures must be adapted to fit the diverse characteristics of study groups	Same metrics can be applied across networks without adjustments, but their accuracy may be undermined
Data Collection	Methods	Both use two types of data collection methods	Measures mainly adopted	Self-report measures	Behavioral measures
			Methods mainly adopted	Survey research	Digital traces data collection
			Attention to data collection	Detailed reporting of participants and data collection procedures	Dataset details and collection methods largely overlooked
Evaluation	Reliability	Both address reliability	Definition of the reliability	Consistency and stability in measuring a construct	Stability of algorithm performance or the continuity of subgroup cohesiveness
			Level of measure reliability	Reliability could be compromised by various sources of errors	Highly reliable due to the automation and objective metric calculation
	Validity	Both consider validity in their evaluation	Objects of evaluation	Cohesion measures	Communities detected/searched by algorithms, from where the measure validity metrics can be inferred
			Perspective of evaluation	Theoretical and empirical	Empirically only, based on the structure and attributes of identified communities

8.3 Discussion

Consistent and accurate cohesion measures are also indispensable for social computing algorithms. However, these studies only validate the superiority of their algorithms through efficiency and effectiveness comparisons [73, 89, 103, 161, 167, 173]. We therefore examine how metrics are evaluated in existing studies through their detection/search result assessments.

Surprisingly, community detection and search rarely address "reliability" in the evaluation. Yet, due to the automated and objective nature of these algorithms, wherein cohesiveness metrics are computed based on established equations rather than relying on participants' limited comprehension or researchers' subjective observations [14], their cohesiveness measurements are always stable and consistent. Regarding validity, we find that the effectiveness evaluation experiments in community detection/search studies are conceptually similar to validity assessments in cohesion studies. However, since cohesion metrics are not directly evaluated in social computing, their validity can only be inferred from the quality of the detected/searched communities: the closer they are to the expected communities, the higher the validity of the metrics.

Generally, retrieved communities are evaluated empirically using four approaches: (1) adopting synthetic network generators for controlled environment testing or ground-truth testing; (2) benchmarking against ground-truth with performance metrics; (3) comparing them with those from other algorithms through a set of "effectiveness metrics" or "goodness metrics", particularly when the ground-truth is unavailable; and (4) conducting case studies to present their interpretability and significance [50, 73, 89, 103, 123, 127, 144, 173]. Popular performance metrics include precision, recall, F-score, accuracy, and Normalized Mutual Information (NMI), which measures the similarity between the set of ground-truth communities and those retrieved by the algorithm [10, 54, 89, 129]. For algorithms that only consider structural cohesiveness metrics, effectiveness are often evaluated based on quantitative attributes of community structure, such as density, clustering coefficient, conductance, triangle participation ratio, diameter, result size, and relationship closeness [8, 10, 36, 89, 104, 122, 133, 189, 215, 218, 226]. For algorithms that incorporate both structural and attribute information, additional metrics are employed, such as semantic richness, average number of activities, community member frequency (CMF), and community pair-wise Jaccard (CPJ) metric [50, 63, 101, 104, 122, 129].

Comparing the evaluation methods between the two fields, it is apparent that their objects of evaluation are different: group cohesion studies focus on the quality of cohesion measures, while social computing emphasizes algorithm performance. Besides, the focus of assessments in social computing studies, similar to the metrics they developed, focuses only on structural and attribute features. While suitable for cohesion definitions rooted in network properties, these methods may be insufficient for capturing psychologically defined cohesion. Currently, no synthetic network generators that incorporate psychological cohesion are available for testing, nor are there datasets with psychologically cohesive communities available for benchmarking. Although efforts have been made to develop effectiveness metrics based on psychological cohesion to compare algorithm-generated communities [229], their quality and generalizability require further validation. With no established standards for cohesion evaluation in social computing, additional metrics are needed to reliably assess psychological cohesion.

Informed by validity assessments in social psychology, cohesiveness metrics should be theoretically evaluated before being integrated into social computing algorithms. This is particularly important when metrics are based on psychological cohesion, as translating such complex constructs into quantifiable measures can be contentious. Without a clear theoretical grounding, metrics may misrepresent or inadequately capture cohesion. In addition, informed by concurrent validity and predictive validity in social psychology, constructs conceptually linked to cohesion, such as morale, group spirit, trust, friendship, and group identification [72, 143], can be quantified as effectiveness metrics, assessing whether identified communities exhibit cohesion-related characteristics or predict future events pertinent to cohesion. Their measurement, as explored in psychological research, could also be examined under our review framework to uncover insights for development.

9 Conclusions

Community detection and search algorithms are key techniques for identifying cohesive subgroups in social applications. However, the concept of cohesion, which originates from social psychology, is not consistently characterized in existing cohesiveness metrics. As a result, these algorithms may fail to identify psychologically cohesive subgroups in online social networks. Given this challenge, this survey reviews cohesion as studied in both social psychology and social computing fields. Following our proposed unified framework, the approach to addressing cohesion in each study is decomposed into four phases encompassing the definition and measurement of cohesion, enabling comparison of their similarities and differences (summarized in Table 9).

We acknowledge several limitations in our review. First, as a narrative rather than a systematic or scoping review, it includes only a representative set of studies and may omit relevant research on cohesion in the two fields. Second, no inter-rater checking was conducted for study selection or evidence validation, which may affect the comprehensiveness of our analysis. Nevertheless, random sampling of eligible papers from the screening process indicates that the identified similarities and differences remain consistent.

Despite these limitations, this survey lays the foundation for integrating social psychological theory into social computing. It offers a fresh perspective on examining community detection and search studies. In addition, our review framework, grounded on social psychology research methods, supports both theory reviews in psychology while serving as an analytical tool for evaluating studies across these traditionally disparate fields. Last but not least, it paves the way for a reevaluation of existing social computing algorithm designs and their practical utility in achieving social application goals.

References

[1] Arni Ahronson and James E Cameron. The nature and consequences of group cohesion in a military sample. *Military psychology*, 19(1):9–25, 2007.

[2] Richard D Alba. A graph-theoretic definition of a sociometric clique. *Journal of Mathematical Sociology*, 3 (1):113–126, 1973.

[3] Maria Altebarmakian and Richard Alterman. Cohesion in online environments. *International Journal of Computer-Supported Collaborative Learning*, 14:443–465, 2019.

[4] Arden J Anderson and Stacy Warner. Social network analysis as a complimentary tool to measuring team cohesion. *Journal of Sport Behavior*, 40(1):3, 2017.

[5] Holly Arrow, Marshall Scott Poole, Kelly Bouas Henry, Susan Wheelan, and Richard Moreland. Time, change, and development: The temporal perspective on groups. *Small group research*, 35(1):73–105, 2004.

[6] CJ Auriacombe. Towards the construction of unobtrusive research techniques: Critical considerations when conducting a literature analysis. *African Journal of Public Affairs*, 9(4):1–19, 2016.

[7] Georgia Baltsou, Konstantinos Christopoulos, and Konstantinos Tsichlas. Local community detection: A survey. *IEEE Access*, 10:110701–110726, 2022.

[8] Nicola Barbieri, Francesco Bonchi, Edoardo Galimberti, and Francesco Gullo. Efficient and effective community search. *Data mining and knowledge discovery*, 29:1406–1433, 2015.

[9] Punam Bedi and Chhavi Sharma. Community detection in social networks. *Wiley interdisciplinary reviews: Data mining and knowledge discovery*, 6(3):115–135, 2016.

[10] Ali Behrouz, Farnoosh Hashemi, and Laks VS Lakshmanan. Firmtruss community search in multilayer networks. *Proceedings of the VLDB Endowment*, 16(3):505–518, 2022.

[11] H Russell Bernard, Peter D Killworth, and Lee Sailer. Informant accuracy in social network data iv: A comparison of clique-level structure in behavioral and cognitive network data. *Social Networks*, 2(3):191–218, 1979.

[12] H Russell Bernard, Peter Killworth, David Kronenfeld, and Lee Sailer. The problem of informant accuracy: The validity of retrospective data. *Annual review of anthropology*, 13(1):495–517, 1984.

[13] Paul R Bernthal and Chester A Insko. Cohesiveness without groupthink: The interactive effects of social and task cohesion. *Group & Organization Management*, 18(1):66–87, 1993.

[14] Anol Bhattacherjee. *Social science research: Principles, methods, and practices.* USA, 2012.

[15] Amy Blackstone. *Principles of sociological inquiry: Qualitative and quantitative methods.* Saylor Academy Open Textbooks, 2018.

[16] Chris Blanchard, Pauline Poon, Wendy Rodgers, and Bruce Pinel. Group environment questionnaire and its applicability in an exercise setting. *Small group research*, 31(2):210–224, 2000.

[17] Paul D Bliese and Ronald R Halverson. Individual and nomothetic models of job stress: An examination of work hours, cohesion, and well-being 1. *Journal of Applied Social Psychology*, 26(13):1171–1189, 1996.

[18] Kenneth A Bollen and Rick H Hoyle. Perceived cohesion: A conceptual and empirical examination. *Social forces*, 69(2):479–504, 1990.

[19] Randa Boukabene and Fatima Benbouzid-Si Tayeb. Community detection metrics in multilayer networks: A survey and novel taxonomy. *SN Computer Science*, 6(5):428, 2025.

[20] Aysun Bozanta, Birgul Kutlu, Nuket Nowlan, and Shervin Shirmohammadi. Effects of serious games on perceived team cohesiveness in a multi-user virtual environment. *Computers in Human Behavior*, 59: 380–388, 2016.

[21] Lawrence R Brawley, Albert V Carron, and W Neil Widmeyer. The influence of the group and its cohesiveness on perceptions of group goal-related variables. *Journal of Sport and Exercise Psychology*, 15 (3):245–260, 1993.

[22] Simon H Budman, Stephen Soldz, Annette Demby, Michael Davis, and Jocelyn Merry. What is cohesiveness? an empirical examination. *Small Group Research*, 24(2):199–216, 1993.

[23] Gary Burlingame, Addie Fuhriman, and Stuart Drescher. Scientific inquiry into small group process: A multidimensional approach. *Small Group Behavior*, 15(4):441–470, 1984.

[24] Yuejun Lawrance Cai. Strengthening perceptions of virtual team cohesiveness and effectiveness in new normal: A hyperpersonal communication theory perspective. *Asian Business & Management*, 22(4): 1649–1682, 2023.

[25] Sally A Carless and Caroline De Paola. The measurement of cohesion in work teams. *Small group research*, 31(1):71–88, 2000.

[26] Albert V Carron. Cohesiveness in sport groups: Interpretations and considerations. *Journal of Sport psychology*, 4(2):123–138, 1982.

[27] Albert V Carron and Lawrence R Brawley. Cohesion: Conceptual and measurement issues. *Small group research*, 31(1):89–106, 2000.

[28] Albert V Carron and Kevin S Spink. The group size-cohesion relationship in minimal groups. *Small group research*, 26(1):86–105, 1995.

[29] Albert V Carron, W Neil Widmeyer, and Lawrence R Brawley. The development of an instrument to assess cohesion in sport teams: The group environment questionnaire. *Journal of Sport and Exercise psychology*, 7 (3):244–266, 1985.

[30] Dorwin Cartwright. The nature of group cohesiveness. *Group dynamics: Research and theory*, 91:109, 1968.

[31] Rich Caruana and Alexandru Niculescu-Mizil. An empirical comparison of supervised learning algorithms. In *Proceedings of the 23rd international conference on Machine learning*, pages 161–168, 2006.

[32] Alberto Castro-Hernández, Kathleen Swigger, and Mirna P Ponce-Flores. Effects of cohesion-based feedback on the collaborations in global software development teams. In *10th IEEE international conference on collaborative computing: Networking, applications and Worksharing*, pages 74–83. IEEE, 2014.

[33] Alberto Castro-Hernández, Kathleen Swigger, Mirna P Ponce-Flores, and J David Terán-Villanueva. Measures for predicting task cohesion in a global collaborative learning environment. In *2016 IEEE 11th International Conference on Global Software Engineering Workshops (ICGSEW)*, pages 31–36. IEEE, 2016.

[34] Artemis Chang and Prashant Bordia. A multidimensional approach to the group cohesion-group performance relationship. *Small group research*, 32(4):379–405, 2001.

[35] Song Chang, Liangding Jia, Riki Takeuchi, and Yahua Cai. Do high-commitment work systems affect creativity? a multilevel combinational approach to employee creativity. *Journal of applied psychology*, 99 (4):665, 2014.

[36] Jiazun Chen, Yikuan Xia, and Jun Gao. Communityaf: An example-based community search method via autoregressive flow. *Proceedings of the VLDB Endowment*, 16(10):2565–2577, 2023.

[37] Jiazun Chen, Yikuan Xia, Jun Gao, Zhao Li, and Hongyang Chen. Communitydf: A guided denoising diffusion approach for community search. In *2025 IEEE 41st International Conference on Data Engineering (ICDE)*, pages 460–473. IEEE Computer Society, 2025.

[38] Jinyi Chen, Junchang Xin, Farhana Choudhury, Keqi Zhou, and Zhiqiong Wang. Efficient stable community search in temporal signed graphs. *Knowledge and Information Systems*, pages 1–31, 2025.

[39] Lu Chen, Chengfei Liu, Rui Zhou, Jianxin Li, Xiaochun Yang, and Bin Wang. Maximum co-located community search in large scale social networks. *Proceedings of the VLDB Endowment*, 11(10):1233–1246, 2018.

[40] Naiyue Chen, Bo Hu, and Yuqun Rui. Dynamic network community detection with coherent neighborhood propinquity. *IEEE Access*, 8:27915–27926, 2020.

[41] David S Chester and Emily N Lasko. Construct validation of experimental manipulations in social psychology: Current practices and recommendations for the future. *Perspectives on Psychological Science*, 16(2):377–395, 2021.

[42] Alvin Chin and Mark Chignell. Automatic detection of cohesive subgroups within social hypertext: A heuristic approach. *New Review of Hypermedia and Multimedia*, 14(1):121–143, 2008.

[43] Wynne W Chin, Wm David Salisbury, Allison W Pearson, and Matthew J Stollak. Perceived cohesion in small groups: Adapting and testing the perceived cohesion scale in a small-group setting. *Small group research*, 30(6):751–766, 1999.

[44] Petr Chunaev. Community detection in node-attributed social networks: a survey. *Computer Science Review*, 37:100286, 2020.

[45] Joshua Cloudy, Melissa R Gotlieb, and Bryan McLaughlin. Online political networks as fertile ground for extremism: The roles of group cohesion and perceived group threat. *Journal of Information Technology & Politics*, 21(4):578–587, 2024.

[46] Jonathan Cohen. Trusses: Cohesive subgraphs for social network analysis. *National security agency technical report*, 16(3.1):1–29, 2008.

[47] Alessio Conte, Daniele De Sensi, Roberto Grossi, Andrea Marino, and Luca Versari. Truly scalable k-truss and max-truss algorithms for community detection in graphs. *IEEE Access*, 8:139096–139109, 2020.

[48] Albert A Cota, Charles R Evans, Kenneth L Dion, Lindy Kilik, and R Stewart Longman. The structure of group cohesion. *Personality and Social Psychology Bulletin*, 21(6):572–580, 1995.

[49] Lee J Cronbach. Coefficient alpha and the internal structure of tests. *psychometrika*, 16(3):297–334, 1951.

[50] Badhan Chandra Das, Md Musfique Anwar, Md Al-Amin Bhuiyan, Iqbal H Sarker, Salem A Alyami, and Mohammad Ali Moni. Attribute driven temporal active online community search. *IEEE Access*, 9: 93976–93989, 2021.

[51] Matthew DeCarlo. *Scientific inquiry in social work*. Open social work education, 2018.

[52] Isabel Dórdio Dimas, Paulo Renato Lourenço, Teresa Rebelo, and Humberto Rocha. Maximizing learning through cohesion: Contributions from a nonlinear approach. *Small Group Research*, 52(2):162–188, 2021.

[53] Kenneth L Dion. Group cohesion: From “field of forces” to multidimensional construct. *Group Dynamics: Theory, research, and practice*, 4(1):7, 2000.

[54] Zheng Dong, Xin Huang, Guorui Yuan, Hengshu Zhu, and Hui Xiong. Butterfly-core community search over labeled graphs. *Proceedings of the VLDB Endowment*, 14(11):2006–2018, 2021.

[55] Stuart Drescher, Gary Burlingame, and Addie Fuhriman. Cohesion: An odyssey in empirical understanding. *Small Group Behavior*, 16(1):3–30, 1985.

[56] Marc Eaton. Manufacturing community in an online activist organization: The rhetoric of moveon. org's e-mails. *Information, Communication & Society*, 13(2):174–192, 2010.

[57] Paul A Estabrooks and Albert V Carron. Group cohesion in older adult exercisers: Prediction and intervention effects. *Journal of behavioral medicine*, 22:575–588, 1999.

[58] Paul A Estabrooks and Albert V Carron. The physical activity group environment questionnaire: An instrument for the assessment of cohesion in exercise classes. *Group Dynamics: Theory, Research, and Practice*, 4(3):230, 2000.

[59] Nancy J Evans and Paul A Jarvis. Group cohesion: A review and reevaluation. *Small group behavior*, 11 (4):359–370, 1980.

[60] Mark Eys, Todd Loughead, Steven R Bray, and Albert V Carron. Development of a cohesion questionnaire for youth: The youth sport environment questionnaire. *Journal of Sport and Exercise Psychology*, 31(3): 390–408, 2009.

[61] Shuheng Fang, Kangfei Zhao, Guanghua Li, and Jeffrey Xu Yu. Community search: a meta-learning approach. In *2023 IEEE 39th International Conference on Data Engineering (ICDE)*, pages 2358–2371. IEEE, 2023.

[62] Shuheng Fang, Kangfei Zhao, Yu Rong, Zhixun Li, and Jeffrey Xu Yu. Inductive attributed community search: to learn communities across graphs. *Proceedings of the VLDB Endowment*, 17(10):2576–2589, 2024.

[63] Yixiang Fang, Reynold Cheng, Siqiang Luo, and Jiafeng Hu. Effective community search for large attributed graphs. *Proceedings of the VLDB Endowment*, 9(12):1233–1244, 2016.

[64] Yixiang Fang, Reynold Cheng, Xiaodong Li, Siqiang Luo, and Jiafeng Hu. Effective community search over large spatial graphs. *Proceedings of the VLDB Endowment*, 10(6):709–720, 2017.

[65] Yixiang Fang, Xin Huang, Lu Qin, Ying Zhang, Wenjie Zhang, Reynold Cheng, and Xuemin Lin. A survey of community search over big graphs. *The VLDB Journal*, 29:353–392, 2020.

[66] Beverley Fehr. *Friendship processes*, volume 12. Sage, 1996.

[67] Scott L Feld and William C Carter. Detecting measurement bias in respondent reports of personal networks. *Social networks*, 24(4):365–383, 2002.

[68] Leon Festinger. The analysis of sociograms using matrix algebra. *Human relations*, 2(2):153–158, 1949.

[69] Leon Festinger. Informal social communication. *Psychological review*, 57(5):271, 1950.

[70] Leon Festinger, Stanley Schachter, and Kurt Back. Social pressures in informal groups; a study of human factors in housing. 1950.

[71] Maria Fors Brandebo, Marcus Börjesson, and Hilmar Hilmarsson. Longitudinal studies on cohesion in a military context–a systematic review. *Military Psychology*, 34(6):732–741, 2022.

[72] Donelson R Forsyth. Recent advances in the study of group cohesion. *Group Dynamics: Theory, Research, and Practice*, 25(3):213, 2021.

[73] Santo Fortunato. Community detection in graphs. *Physics reports*, 486(3-5):75–174, 2010.

[74] Santo Fortunato and Darko Hric. Community detection in networks: A user guide. *Physics reports*, 659: 1–44, 2016.

[75] Santo Fortunato, Vito Latora, and Massimo Marchiori. Method to find community structures based on information centrality. *Physical review E*, 70(5):056104, 2004.

[76] Borko Furht. *Handbook of social network technologies and applications*. Springer Science & Business Media, 2010.

[77] Jun Gao, Jiazun Chen, Zhao Li, and Ji Zhang. Ics-gnn: lightweight interactive community search via graph neural network. *Proceedings of the VLDB Endowment*, 14(6):1006–1018, 2021.

[78] David Gefen and Detmar Straub. A practical guide to factorial validity using pls-graph: Tutorial and annotated example. *Communications of the Association for Information systems*, 16(1):5, 2005.

[79] Shreya Ghosh, Abhinav Dhall, Nicu Sebe, and Tom Gedeon. Predicting group cohesiveness in images. In *2019 International Joint Conference on Neural Networks (IJCNN)*, pages 1–8. IEEE, 2019.

[80] Pablo M Gleiser and Leon Danon. Community structure in jazz. *Advances in complex systems*, 6(04): 565–573, 2003.

[81] Amy L Gonzales, Jeffrey T Hancock, and James W Pennebaker. Language style matching as a predictor of social dynamics in small groups. *Communication Research*, 37(1):3–19, 2010.

[82] Ilanit Gordon, Avi Gilboa, Shai Cohen, Nir Milstein, Nir Haimovich, Shay Pinhasi, and Shahar Siegman. Physiological and behavioral synchrony predict group cohesion and performance. *Scientific reports*, 10(1): 8484, 2020.

[83] Lindred L Greer. Group cohesion: Then and now. *Small Group Research*, 43(6):655–661, 2012.

[84] James Griffith. Measurement of group cohesion in us army units. *Basic and applied social psychology*, 9(2): 149–171, 1988.

[85] Natali Gulbahce and Sune Lehmann. The art of community detection. *BioEssays*, 30(10):934–938, 2008.

[86] Da Guo, Kai Wang, Jianfei Yang, Kaipeng Zhang, Xiaojiang Peng, and Yu Qiao. Exploring regularizations with face, body and image cues for group cohesion prediction. In *2019 International Conference on Multimodal Interaction*, pages 557–561, 2019.

[87] Zixiu Guo, Felix B Tan, Tim Turner, and Huizhong Xu. Group norms, media preferences, and group meeting success: A longitudinal study. *Computers in Human Behavior*, 26(4):645–655, 2010.

[88] James Hardy, Mark A Eys, and Albert V Carron. Exploring the potential disadvantages of high cohesion in sports teams. *Small group research*, 36(2):166–187, 2005.

[89] Steve Harenberg, Gonzalo Bello, La Gjeltema, Stephen Ranshous, Jitendra Harlalka, Ramona Seay, Kanchana Padmanabhan, and Nagiza Samatova. Community detection in large-scale networks: a survey and empirical evaluation. *Wiley Interdisciplinary Reviews: Computational Statistics*, 6(6):426–439, 2014.

[90] Farnoosh Hashemi, Ali Behrouz, and Milad Rezaei Hajidehi. Cs-tgn: Community search via temporal graph neural networks. In *Companion Proceedings of the ACM Web Conference 2023*, pages 1196–1203, 2023.

[91] Chaobo He, Junwei Cheng, Guohua Chen, and Yong Tang. Multiple topics community detection in attributed networks. In *Proceedings of the 46th International ACM SIGIR Conference on Research and Development in Information Retrieval*, pages 2199–2203, 2023.

[92] RA Hinde and Joan Stevenson-Hinde. Towards understanding relationships: Dynamic stability. 1976.

[93] Christine Hine. Internet research and unobtrusive methods. *Social Research Update*, (61):1, 2011.

[94] Martin Hoegl and Hans Georg Gemuenden. Teamwork quality and the success of innovative projects: A theoretical concept and empirical evidence. *Organization science*, 12(4):435–449, 2001.

[95] Michael A Hogg. The social psychology of group cohesiveness: From attraction to social identity. 1992.

[96] Michael A Hogg. Group cohesiveness: A critical review and some new directions. *European review of social psychology*, 4(1):85–111, 1993.

[97] Michael A Hogg and Sarah C Hains. Friendship and group identification: A new look at the role of cohesiveness in groupthink. *European journal of social psychology*, 28(3):323–341, 1998.

[98] Xinyu Huang, Dongming Chen, Tao Ren, and Dongqi Wang. A survey of community detection methods in multilayer networks. *Data Mining and Knowledge Discovery*, 35:1–45, 2021.

[99] Hayley Hung and Daniel Gatica-Perez. Estimating cohesion in small groups using audio-visual nonverbal behavior. *IEEE Transactions on Multimedia*, 12(6):563–575, 2010.

[100] Isa Inuwa-Dutse, Mark Liptrott, and Ioannis Korkontzelos. A multilevel clustering technique for community detection. *Neurocomputing*, 441:64–78, 2021.

[101] Md Saiful Islam, Mohammed Eunus Ali, Yong-Bin Kang, Timos Sellis, Farhana M Choudhury, and Shamik Roy. Keyword aware influential community search in large attributed graphs. *Information Systems*, 104: 101914, 2022.

[102] Devi Jankowicz. *The easy guide to repertory grids*. John wiley & sons, 2005.

[103] Muhammad Aqib Javed, Muhammad Shahzad Younis, Siddique Latif, Junaid Qadir, and Adeel Baig. Community detection in networks: A multidisciplinary review. *Journal of Network and Computer Applications*, 108:87–111, 2018.

[104] Yangqin Jiang, Yixiang Fang, Chenhao Ma, Xin Cao, and Chunshan Li. Effective community search over large star-schema heterogeneous information networks. *Proceedings of the VLDB Endowment*, 15(11): 2307–2320, 2022.

[105] Yuli Jiang, Yu Rong, Hong Cheng, Xin Huang, Kangfei Zhao, and Junzhou Huang. Query driven-graph neural networks for community search: from non-attributed, attributed, to interactive attributed. *Proceedings of the VLDB Endowment*, 15(6):1243–1255, 2022.

[106] Di Jin, Zhizhi Yu, Pengfei Jiao, Shirui Pan, Dongxiao He, Jia Wu, Philip S Yu, and Weixiong Zhang. A survey of community detection approaches: From statistical modeling to deep learning. *IEEE Transactions on knowledge and data engineering*, 35(2):1149–1170, 2021.

[107] Dong I Jung and John J Sosik. Transformational leadership in work groups: The role of empowerment, cohesiveness, and collective-efficacy on perceived group performance. *Small group research*, 33(3):313–336, 2002.

[108] Mark Keith, Greg Anderson, Douglas Dean, James Gaskin, Trevor Wiser, and Seth Gremmert. The effects of video gaming on work group performance. 2016.

[109] Mark J Keith, Greg Anderson, James Gaskin, and Douglas L Dean. Team video gaming for team building: Effects on team performance. *AIS Transactions on Human-Computer Interaction*, 10(4):205–231, 2018.

[110] Stephen Kelley, Mark Goldberg, Malik Magdon-Ismail, Konstantin Mertsalov, and Al Wallace. Defining and discovering communities in social networks. *Handbook of optimization in complex networks: Theory and applications*, 57:139–168, 2012.

[111] Florian Keusch and Frauke Kreuter. Digital trace data: Modes of data collection, applications, and errors at a glance. In *Handbook of Computational Social Science, Vol 1*. Taylor & Francis, 2021.

[112] Christine Klymko, David Gleich, and Tamara G Kolda. Using triangles to improve community detection in directed networks. *arXiv preprint arXiv:1404.5874*, 2014.

[113] David Knoke and Song Yang. *Social network analysis*. SAGE publications, 2019.

[114] Tetsuro Kobayashi, Ken'ichi Ikeda, and Kakuko Miyata. Social capital online: Collective use of the internet and reciprocity as lubricants of democracy. *Information, Community & Society*, 9(5):582–611, 2006.

[115] Steve WJ Kozlowski. Advancing research on team process dynamics: Theoretical, methodological, and measurement considerations. *Organizational Psychology Review*, 5(4):270–299, 2015.

[116] Steve WJ Kozlowski and Georgia T Chao. The dynamics of emergence: Cognition and cohesion in work teams. *Managerial and Decision Economics*, 33(5-6):335–354, 2012.

[117] Steve WJ Kozlowski and Katherine J Klein. A multilevel approach to theory and research in organizations: Contextual, temporal, and emergent processes. 2000.

[118] Claus W Langfred. Is group cohesiveness a double-edged sword? an investigation of the effects of cohesiveness on performance. *Small Group Research*, 29(1):124–143, 1998.

[119] Neuman W Lawrence. Basics of social research: Qualitative and quantitative approaches, 2007.

[120] Matthew D Lerner, Bryce D McLeod, and Amori Y Mikami. Preliminary evaluation of an observational measure of group cohesion for group psychotherapy. *Journal of Clinical Psychology*, 69(3):191–208, 2013.

[121] Jure Leskovec, Jon Kleinberg, and Christos Faloutsos. Graph evolution: Densification and shrinking diameters. *ACM transactions on Knowledge Discovery from Data (TKDD)*, 1(1):2–es, 2007.

[122] Conggai Li, Fan Zhang, Ying Zhang, Lu Qin, Wenjie Zhang, and Xuemin Lin. Efficient progressive minimum k-core search. *Proceedings of the VLDB Endowment*, 13(3):362–375, 2019.

[123] Jianxin Li, Xinjue Wang, Ke Deng, Xiaochun Yang, Timos Sellis, and Jeffrey Xu Yu. Most influential community search over large social networks. In *2017 IEEE 33rd international conference on data engineering (ICDE)*, pages 871–882, San Diego, CA, USA, 2017. IEEE.

[124] Ling Li, Siqiang Luo, Yuhai Zhao, Caihua Shan, Zhengkui Wang, and Lu Qin. Coclep: Contrastive learning-based semi-supervised community search. In *2023 IEEE 39th International Conference on Data Engineering (ICDE)*, pages 2483–2495. IEEE, 2023.

[125] Rong-Hua Li, Lu Qin, Jeffrey Xu Yu, and Rui Mao. Influential community search in large networks. *Proceedings of the VLDB Endowment*, 8(5):509–520, 2015.

[126] Rong-Hua Li, Lu Qin, Fanghua Ye, Jeffrey Xu Yu, Xiaokui Xiao, Nong Xiao, and Zibin Zheng. Skyline community search in multi-valued networks. In *Proceedings of the 2018 international conference on management of data*, pages 457–472, 2018.

[127] Rong-Hua Li, Jiao Su, Lu Qin, Jeffrey Xu Yu, and Qiangqiang Dai. Persistent community search in temporal networks. In *2018 IEEE 34th International Conference on Data Engineering (ICDE)*, pages 797–808, Paris, France, 2018. IEEE.

[128] Kwan Hui Lim and Amitava Datta. An interaction-based approach to detecting highly interactive twitter communities using tweeting links. In *Web Intelligence*, volume 14, pages 1–15. IOS Press, 2016.

[129] Qing Liu, Minjun Zhao, Xin Huang, Jianliang Xu, and Yunjun Gao. Truss-based community search over large directed graphs. In *Proceedings of the 2020 ACM SIGMOD International Conference on Management of Data*, pages 2183–2197, 2020.

[130] Albert J Lott and Bernice E Lott. Group cohesiveness as interpersonal attraction: A review of relationships with antecedent and consequent variables. *Psychological bulletin*, 64(4):259, 1965.

[131] Bernice E Lott. Group cohesiveness, communication level, and conformity. *The Journal of Abnormal and Social Psychology*, 62(2):408, 1961.

[132] Lin Lu and Kui Xie. Achievement goals and team leadership in online small group learning. International Society of the Learning Sciences, Inc.[ISLS]., 2018.

[133] Zhao Lu, Yuanyuan Zhu, Ming Zhong, and Jeffrey Xu Yu. On time-optimal (k, p)-core community search in dynamic graphs. In *2022 IEEE 38th International Conference on Data Engineering (ICDE)*, pages 1396–1407, Kuala Lumpur, Malaysia, 2022. IEEE.

[134] R Duncan Luce and Albert D Perry. A method of matrix analysis of group structure. *Psychometrika*, 14 (2):95–116, 1949.

[135] Chengyang Luo, Qing Liu, Yunjun Gao, and Jianliang Xu. Synergetic community search over large multilayer graphs. 18(6):1412–1424, 2025. doi: 10.14778/3718057.3718069.

[136] Annmarie A Lyles, Colleen Loomis, Scherezade K Mama, Sameer Siddiqi, and Rebecca E Lee. Longitudinal analysis of virtual community perceptions of cohesion: The role of cooperation, communication, and competition. *Journal of Health Psychology*, 23(13):1677–1688, 2018.

[137] Merce Mach, Simon Dolan, and Shay Tzafrir. The differential effect of team members' trust on team performance: The mediation role of team cohesion. *Journal of occupational and organizational psychology*, 83(3):771–794, 2010.

[138] Omid Madani, Sai Ankith Averineni, and Shashidhar Gandham. A dataset of networks of computing hosts. In *Proceedings of the 2022 ACM on International Workshop on Security and Privacy Analytics*, pages 100–104, 2022.

[139] Lucien Maman, Eleonora Ceccaldi, Nale Lehmann-Willenbrock, Laurence Likforman-Sulem, Mohamed Chetouani, Gualtiero Volpe, and Giovanna Varni. Game-on: A multimodal dataset for cohesion and group analysis. *IEEE Access*, 8:124185–124203, 2020.

[140] Michelle A Marks, John E Mathieu, and Stephen J Zaccaro. A temporally based framework and taxonomy of team processes. *Academy of management review*, 26(3):356–376, 2001.

[141] Peter V Marsden. Network data and measurement. *Annual review of sociology*, 16(1):435–463, 1990.

[142] Peter V Marsden. Recent developments in network measurement. *Models and methods in social network analysis*, 8:30, 2005.

[143] Janet McLeod and Kathryn Von Treuer. Towards a cohesive theory of cohesion. 2013.

[144] Xiaoye Miao, Yue Liu, Lu Chen, Yunjun Gao, and Jianwei Yin. Reliable community search on uncertain graphs. In *2022 IEEE 38th International Conference on Data Engineering (ICDE)*, pages 1166–1179, Kuala Lumpur, Malaysia, 2022. IEEE.

[145] Ron Milo, Shai Shen-Orr, Shalev Itzkovitz, Nadav Kashtan, Dmitri Chklovskii, and Uri Alon. Network motifs: simple building blocks of complex networks. *Science*, 298(5594):824–827, 2002.

[146] EL-MOUSSAOUI Mohamed, Tarik Agouti, Abdessadek Tikniouine, and Mohamed El Adnani. A comprehensive literature review on community detection: Approaches and applications. *Procedia Computer Science*, 151:295–302, 2019.

[147] Dan Mønster, Dorthe Døjbak Håkonsson, Jacob Kjær Eskildsen, and Sebastian Wallot. Physiological evidence of interpersonal dynamics in a cooperative production task. *Physiology & behavior*, 156:24–34, 2016.

[148] Christian Montag, Éilish Duke, and Alexander Markowetz. Toward psychoinformatics: Computer science meets psychology. *Computational and mathematical methods in medicine*, 2016(1):2983685, 2016.

[149] Peter E Mudrack. Defining group cohesiveness: A legacy of confusion? *Small group behavior*, 20(1):37–49, 1989.

[150] Sean A Munson, Karina Kervin, and Lionel P Robert Jr. Monitoring email to indicate project team performance and mutual attraction. In *Proceedings of the 17th ACM conference on Computer supported cooperative work & social computing*, pages 542–549, 2014.

[151] Mansoureh Naderipour, Mohammad Hossein Fazel Zarandi, and Susan Bastani. Fuzzy community detection on the basis of similarities in structural/attribute in large-scale social networks. *Artificial Intelligence Review*, 55:1373–1407, 2022.

[152] W Lawrence Neuman. *Basics of social research*. 2007.

[153] Mark EJ Newman and Michelle Girvan. Finding and evaluating community structure in networks. *Physical review E*, 69(2):026113, 2004.

[154] Kate G Niederhoffer and James W Pennebaker. Linguistic style matching in social interaction. *Journal of Language and Social Psychology*, 21(4):337–360, 2002.

[155] Robert Z Norman et al. Structural models: An introduction to the theory of directed graphs. 1965.

[156] J.C. Nunnally. *Psychometric Theory*. McGraw-Hill series in psychology. McGraw-Hill, 1978.

[157] Leysan Nurgalieva, Alisa Frik, and Gavin Doherty. A narrative review of factors affecting the implementation of privacy and security practices in software development. *ACM Computing Surveys*, 55(14s):1–27, 2023.

[158] Jakob Ohme, Theo Araujo, Laura Boeschoten, Deen Freelon, Nilam Ram, Byron B Reeves, and Thomas N Robinson. Digital trace data collection for social media effects research: Apis, data donation, and (screen) tracking. *Communication Methods and Measures*, 18(2):124–141, 2024. doi: 10.1080/19312458.2023.2181319.

[159] Laurel W Oliver, Joan Harman, Elizabeth Hoover, Stephanie M Hayes, and Nancy A Pandhi. A quantitative integration of the military cohesion literature. *Military Psychology*, 11(1):57–83, 1999.

[160] Matthew J Page, Joanne E McKenzie, Patrick M Bossuyt, Isabelle Boutron, Tammy C Hoffmann, Cynthia D Mulrow, Larissa Shamseer, Jennifer M Tetzlaff, Elie A Akl, Sue E Brennan, Roger Chou, Julie Glanville, Jeremy M Grimshaw, Asbjørn Hróbjartsson, Manoj M Lalu, Tianjing Li, Elizabeth W Loder, Evan Mayo-Wilson, Steve McDonald, Luke A McGuinness, Lesley A Stewart, James Thomas, Andrea C Tricco, Vivian A Welch, Penny Whiting, and David Moher. The prisma 2020 statement: an updated guideline for reporting systematic reviews. *BMJ*, 372, 2021. doi: 10.1136/bmj.n71. URL `https://www.bmj.com/content/372/bmj.n71`.

[161] Symeon Papadopoulos, Yiannis Kompatsiaris, Athena Vakali, and Ploutarchos Spyridonos. Community detection in social media: Performance and application considerations. *Data mining and knowledge discovery*, 24:515–554, 2012.

[162] Manoj Parameswaran and Andrew B Whinston. Social computing: An overview. *Communications of the association for Information Systems*, 19(1):37, 2007.

[163] Guy Paré, Marie-Claude Trudel, Mirou Jaana, and Spyros Kitsiou. Synthesizing information systems knowledge: A typology of literature reviews. *Information & management*, 52(2):183–199, 2015.

[164] Ravi Paul, John R Drake, and Huigang Liang. Global virtual team performance: The effect of coordination effectiveness, trust, and team cohesion. *IEEE Transactions on Professional Communication*, 59(3):186–202, 2016.

[165] Delroy L Paulhus, Simine Vazire, et al. The self-report method. *Handbook of research methods in personality psychology*, 1(2007):224–239, 2007.

[166] Anthony T Pescosolido and Richard Saavedra. Cohesion and sports teams: A review. *Small Group Research*, 43(6):744–758, 2012.

[167] Michel Plantié and Michel Crampes. Survey on social community detection. In *Social media retrieval*, pages 65–85. Springer, 2012.

[168] Matthew S Prewett. Clarifying the cohesion-performance relationship in teams: Backup behavior as a mediating mechanism. 2006.

[169] Ioannis Psorakis, Stephen Roberts, Mark Ebden, and Ben Sheldon. Overlapping community detection using bayesian non-negative matrix factorization. *Physical Review E*, 83(6):066114, 2011.

[170] Meng Qin, Chaorui Zhang, Yu Gao, Weixi Zhang, and Dit-Yan Yeung. Pre-train and refine: Towards higher efficiency in k-agnostic community detection without quality degradation. In *Proceedings of the 30th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*, pages 2467–2478, 2024.

[171] Anat Rafaeli, Shelly Ashtar, and Daniel Altman. Digital traces: New data, resources, and tools for psychological-science research. *Current directions in psychological science*, 28(6):560–566, 2019.

[172] Donald J Rose. On simple characterizations of k-trees. *Discrete mathematics*, 7(3-4):317–322, 1974.

[173] Giulio Rossetti and Rémy Cazabet. Community discovery in dynamic networks: a survey. *ACM computing surveys (CSUR)*, 51(2):1–37, 2018.

[174] Eduardo Salas, Dana E Sims, and C Shawn Burke. Is there a "big five" in teamwork? *Small group research*, 36(5):555–599, 2005.

[175] Eduardo Salas, Rebecca Grossman, Ashley M Hughes, and Chris W Coultas. Measuring team cohesion: Observations from the science. *Human factors*, 57(3):365–374, 2015.

[176] Wm David Salisbury, Traci A Carte, and Laku Chidambaram. Cohesion in virtual teams: validating the perceived cohesion scale in a distributed setting. *ACM SIGMIS Database: the DATABASE for Advances in Information Systems*, 37(2-3):147–155, 2006.

[177] Jessica M Santoro, Aurora J Dixon, Chu-Hsiang Chang, and Steve WJ Kozlowski. Measuring and monitoring the dynamics of team cohesion: Methods, emerging tools, and advanced technologies. In *Team cohesion: Advances in psychological theory, methods and practice*, pages 115–145. Emerald Group Publishing Limited, Leeds, 2015.

[178] Jürgen Schmidhuber. Deep learning in neural networks: An overview. *Neural networks*, 61:85–117, 2015.

[179] Stanley Emanuel Seashore. *Group cohesiveness in the industrial work group*. University of Michigan Ann Arbor, 1954.

[180] Stephen B Seidman. Network structure and minimum degree. *Social networks*, 5(3):269–287, 1983.

[181] Stephen B Seidman and Brian L Foster. A graph-theoretic generalization of the clique concept. *Journal of Mathematical sociology*, 6(1):139–154, 1978.

[182] Junming Shao, Zhichao Han, Qinli Yang, and Tao Zhou. Community detection based on distance dynamics. In *Proceedings of the 21th ACM SIGKDD international conference on knowledge discovery and data mining*, pages 1075–1084, 2015.

[183] John J Shaughnessy, Eugene B Zechmeister, and Jeanne S Zechmeister. *Research methods in psychology*. McGraw-Hill, 2000.

[184] Kelly G Shaver. *Principles of social psychology*. Psychology Press, 2015.

[185] Valerie Sheppard. Research methods for the social sciences: An introduction. *Vancouver: BCCampus*, 2020.

[186] Jessica Shi, Laxman Dhulipala, David Eisenstat, Jakub Łăcki, and Vahab Mirrokni. Scalable community detection via parallel correlation clustering. *Proceedings of the VLDB Endowment*, 14(11):2305–2313, 2021.

[187] JinNuo Shi. A hierarchical model for community identification in complex networks through modularity and genetic algorithm. *Scientific Reports*, 15(1):1–21, 2025.

[188] Yuhyung Shin and Kyojik Song. Role of face-to-face and computer-mediated communication time in the cohesion and performance of mixed-mode groups. *Asian Journal of Social Psychology*, 14(2):126–139, 2011.

[189] Mauro Sozio and Aristides Gionis. The community-search problem and how to plan a successful cocktail party. In *Proceedings of the 16th ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 939–948, 2010.

[190] Tobias H. Stark. Collecting social network data. pages 241–254, 2018.

[191] Xing Su, Shan Xue, Fanzhen Liu, Jia Wu, Jian Yang, Chuan Zhou, Wenbin Hu, Cecile Paris, Surya Nepal, Di Jin, et al. A comprehensive survey on community detection with deep learning. *IEEE transactions on neural networks and learning systems*, 35(4):4682–4702, 2022.

[192] Isabelle Szmigin, Louise Canning, and Alexander E Reppel. Online community: enhancing the relationship marketing concept through customer bonding. *International journal of service industry management*, 16(5): 480–496, 2005.

[193] Keith S Taber. The use of cronbach's alpha when developing and reporting research instruments in science education. *Research in science education*, 48:1273–1296, 2018.

[194] Yifu Tang, Jianxin Li, Nur Al Hasan Haldar, Ziyu Guan, Jiajie Xu, and Chengfei Liu. Reliable community search in dynamic networks. *Proceedings of the VLDB Endowment*, 15(11):2826–2838, 2022.

[195] Claire Thornton, Phillip Miller, and Kelly Perry. The impact of group cohesion on key success measures in higher education. *Journal of Further and Higher Education*, 44(4):542–553, 2020.

[196] Alon Tomashin, Ilanit Gordon, and Sebastian Wallot. Interpersonal physiological synchrony predicts group cohesion. *Frontiers in human neuroscience*, 16:903407, 2022.

[197] Bruce W Tuckman and Mary Ann C Jensen. Stages of small-group development revisited. *Group & organization studies*, 2(4):419–427, 1977.

[198] Mark Vaitkus and James Griffith. An evaluation of unit replacement on unit cohesion and individual morale in the us army all-volunteer force. *Military Psychology*, 2(4):221–239, 1990.

[199] Judy L Van Raalte, Allen E Cornelius, Darwyn E Linder, and Britton W Brewer. The relationship between hazing and team cohesion. *Journal of sport behavior*, 30(4):491, 2007.

[200] Kathryn Von Treuer, Janet McLeod, Matthew Fuller-Tyszkiewicz, and Graham Scott. Determining the components of cohesion using the repertory grid technique. *Group Dynamics: Theory, Research, and Practice*, 22(2):108, 2018.

[201] Fabian Walocha, Lucien Maman, Mohamed Chetouani, and Giovanna Varni. Modeling dynamics of task and social cohesion from the group perspective using nonverbal motion capture-based features. In *Companion publication of the 2020 international conference on multimodal interaction*, pages 182–190, 2020.

[202] Eric Wang, Huey-Wen Chou, and James Jiang. The impacts of charismatic leadership style on team cohesiveness and overall performance during erp implementation. *International Journal of Project Management*, 23(3):173–180, 2005.

[203] Fei-Yue Wang, Kathleen M Carley, Daniel Zeng, and Wenji Mao. Social computing: From social informatics to social intelligence. *IEEE Intelligent systems*, 22(2):79–83, 2007.

[204] Jianwei Wang, Kai Wang, Xuemin Lin, Wenjie Zhang, and Ying Zhang. Efficient unsupervised community search with pre-trained graph transformer. *Proceedings of the VLDB Endowment*, 17(9):2227–2240, 2024.

[205] Jianwei Wang, Kai Wang, Xuemin Lin, Wenjie Zhang, and Ying Zhang. Neural attributed community search at billion scale. *Proceedings of the ACM on Management of Data*, 1(4):1–25, 2024.

[206] Yue Wang, Xun Jian, Zhenhua Yang, and Jia Li. Query optimal k-plex based community in graphs. *Data Science and Engineering*, 2:257–273, 2017.

[207] Yuxiang Wang, Xiaoxuan Gou, Xiaoliang Xu, Yuxia Geng, Xiangyu Ke, Tianxing Wu, Zhiyuan Yu, Runhuai Chen, and Xiangying Wu. Scalable community search over large-scale graphs based on graph transformer. In *Proceedings of the 47th International ACM SIGIR Conference on Research and Development in Information Retrieval*, pages 1680–1690, 2024.

[208] Stanley Wasserman and Katherine Faust. Social network analysis: Methods and applications. 1994.

[209] Robert S Weiss and Eugene Jacobson. A method for the analysis of the structure of complex organizations. *American Sociological Review*, 20(6):661–668, 1955.

[210] Joyce Jiyoung Whang, David F Gleich, and Inderjit S Dhillon. Overlapping community detection using neighborhood-inflated seed expansion. *IEEE Transactions on Knowledge and Data Engineering*, 28(5): 1272–1284, 2016.

[211] Xixi Wu, Yun Xiong, Yao Zhang, Yizhu Jiao, Caihua Shan, Yiheng Sun, Yangyong Zhu, and Philip S Yu. Clare: A semi-supervised community detection algorithm. In *Proceedings of the 28th ACM SIGKDD conference on knowledge discovery and data mining*, pages 2059–2069, 2022.

[212] Xixi Wu, Kaiyu Xiong, Yun Xiong, Xiaoxin He, Yao Zhang, Yizhu Jiao, and Jiawei Zhang. Procom: A few-shot targeted community detection algorithm. In *Proceedings of the 30th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*, pages 3414–3424, 2024.

[213] Yantuan Xian, Pu Li, Hao Peng, Zhengtao Yu, Yan Xiang, and Philip S Yu. Community detection in large-scale complex networks via structural entropy game. In *Proceedings of the ACM on Web Conference 2025*, pages 3930–3941, 2025.

[214] Kui Xie, Lauren C Hensley, Victor Law, and Zhiru Sun. Self-regulation as a function of perceived leadership and cohesion in small group online collaborative learning. *British Journal of Educational Technology*, 50(1): 456–468, 2019.

[215] Tianyang Xu, Zhao Lu, and Yuanyuan Zhu. Efficient triangle-connected truss community search in dynamic graphs. *Proceedings of the VLDB Endowment*, 16(3):519–531, 2022.

[216] Jaewon Yang and Jure Leskovec. Defining and evaluating network communities based on ground-truth. In *Proceedings of the ACM SIGKDD workshop on mining data semantics*, pages 1–8, 2012.

[217] Jaewon Yang, Julian McAuley, and Jure Leskovec. Detecting cohesive and 2-mode communities indirected and undirected networks. In *Proceedings of the 7th ACM international conference on Web search and data mining*, pages 323–332, 2014.

[218] Kai Yao and Lijun Chang. Efficient size-bounded community search over large networks. *Proceedings of the VLDB Endowment*, 14(8):1441–1453, 2021.

[219] Hao Yin, Austin R Benson, Jure Leskovec, and David F Gleich. Local higher-order graph clustering. In *Proceedings of the 23rd ACM SIGKDD international conference on knowledge discovery and data mining*, pages 555–564, 2017.

[220] Youngjin Yoo and Maryam Alavi. Media and group cohesion: Relative influences on social presence, task participation, and group consensus. *MIS quarterly*, pages 371–390, 2001.

[221] Xin Yu, Jing Yang, and Zhi-Qiang Xie. A semantic overlapping community detection algorithm based on field sampling. *Expert Systems with Applications*, 42(1):366–375, 2015.

[222] Stephen J Zaccaro and Charles A Lowe. Cohesiveness and performance on an additive task: Evidence for multidimensionality. *The Journal of Social Psychology*, 128(4):547–558, 1988.

[223] Wayne W Zachary. An information flow model for conflict and fission in small groups. *Journal of anthropological research*, 33(4):452–473, 1977.

[224] Andrew Zamecnik, Cristina Villa-Torrano, Vitomir Kovanović, Georg Grossmann, Srećko Joksimović, Yannis Dimitriadis, and Abelardo Pardo. The cohesion of small groups in technology-mediated learning environments: A systematic literature review. *Educational Research Review*, 35:100427, 2022.

[225] Andrew Zamecnik, Vitomir Kovanovíc, Srécko Joksimovíc, Georg Grossmann, Djazia Ladjal, Ruth Marshall, and Abelardo Pardo. Using online learner trace data to understand the cohesion of teams in higher education. *Journal of Computer Assisted Learning*, 39(6):1733–1750, 2023.

[226] Fan Zhang, Haicheng Guo, Dian Ouyang, Shiyu Yang, Xuemin Lin, and Zhihong Tian. Size-constrained community search on large networks: An effective and efficient solution. *IEEE Transactions on Knowledge and Data Engineering*, 36(1):356–371, 2024.

[227] Yanxia Zhang, Jeffrey Olenick, Chu-Hsiang Chang, Steve WJ Kozlowski, and Hayley Hung. Teamsense: assessing personal affect and group cohesion in small teams through dyadic interaction and behavior analysis with wearable sensors. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, 2(3):1–22, 2018.

[228] Yao Zhang, Yun Xiong, Yun Ye, Tengfei Liu, Weiqiang Wang, Yangyong Zhu, and Philip S Yu. Seal: Learning heuristics for community detection with generative adversarial networks. In *Proceedings of the 26th ACM SIGKDD international conference on knowledge discovery & data mining*, pages 1103–1113, 2020.

[229] Yining Zhao, Sourav S Bhowmick, Fischer Nastassja L., and SH Annabel Chen. How cohesive are community search results on online social networks?: An experimental evaluation. In *Proceedings of the 48th International ACM SIGIR Conference on Research and Development in Information Retrieval*, SIGIR '25, New York, NY, USA, 2025. Association for Computing Machinery.

[230] Yu Zhao, Mark Srite, Sumin Kim, and Jinwoong Lee. Effect of team cohesion on flow: An empirical study of team-based gamification for enterprise resource planning systems in online classes. *Decision Sciences Journal of Innovative Education*, 19(3):173–184, 2021.

[231] Lanqin Zheng and Lanqin Zheng. A socially shared regulation approach to improving group cohesion, collective efficacy, and regulation skills in cscl. *Knowledge building and regulation in computer-supported collaborative learning*, pages 83–96, 2017.

[232] Lanqin Zheng, Ronghuai Huang, and Junhui Yu. The impact of different roles on motivation, group cohesion, and learning performance in computer-supported collaborative learning (cscl). In *2014 IEEE 14th International Conference on Advanced Learning Technologies*, pages 294–296, Athens, Greece, 2014. IEEE.

[233] Rui Zhou, Chengfei Liu, Jeffrey Xu Yu, Weifa Liang, Baichen Chen, and Jianxin Li. Finding maximal k-edge-connected subgraphs from a large graph. In *Proceedings of the 15th international conference on extending database technology*, pages 480–491, 2012.

[234] Zhijian Zhuo, Bilian Chen, Shenbao Yu, and Langcai Cao. Overlapping community detection using expansion with contraction. *Neurocomputing*, 565:126989, 2024.

[235] Philip G Zimbardo, Robert Lee Johnson, Vivian McCann, and Carol Carter. *Psychology: core concepts*. Allyn and Bacon Boston, 2003.