Towards a Dynamic Model of Collective Intelligence: Theoretical Integration, Nonverbal Interaction and Temporality

TRISTAN LANNUZEL, BEATRICE BIANCARDI, MUKESH BARANGE, and STÉPHANIE BUISINE, CESI, LINEACT, France

Most existing research on Collective Intelligence (CI) tends to emphasize final performance indicators or sums of individual cognitive traits, giving insufficient attention to how teams dynamically construct their collective capacity through ongoing interactions. In this paper, we propose an integrative perspective that draws on multiple existing approaches, ranging from conceptual frameworks (IMOI, TSM-CI) to measurement-oriented constructs (C-factor, synergy) and team cognition, while underscoring the essential behavioral and temporal processes that drive collective intelligence. Rather than viewing collective intelligence as a static end-point, our model explores how nonverbal cues (e.g., posture, gaze, interpersonal distance), repeated feedback loops, and macro-level temporal dynamics converge to shape a team's coordination, cohesion, and shared use of knowledge. By highlighting the continuous, real-time mechanisms through which teams adapt, self-regulate, and refine their performance, we address the need for a more process-oriented, longitudinal perspective. We also propose practical methodological pathways to more accurately capture how teams evolve from loosely connected individuals into high-performing collectives over time.

CCS Concepts: • **Human-centered computing → Collaborative and social computing theory, concepts and paradigms**; • **Applied computing → Psychology**.

Additional Key Words and Phrases: **Keywords**: Collective Intelligence, Nonverbal Communication, Transactive Systems, Interaction Processes

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1 Introduction

Collective intelligence (CI), described as a group's or team's general capacity to accomplish a wide variety of tasks [60], is currently generating considerable interest in fields as diverse as management, communication, information sciences, and work psychology [21]. Given the major challenges facing human groups, the need to strengthen this capacity is becoming increasingly strategic, both now and in the years to come. However, before exploring concrete solutions, it is important to develop a dynamic theoretical model that allows us to understand collective intelligence as a process of construction and evolution, rather than as a fixed state.

Yet, the diversity of existing approaches can lead to a fragmentation of perspectives, complicating the formulation of a coherent framework. Many studies approach collective intelligence primarily through outcome-based assessments,

Authors' Contact Information: Tristan Lannuzel, tlannuzel@cesi.fr; Beatrice Biancardi, bbiancardi@cesi.fr; Mukesh Barange, mbarange@cesi.fr; Stéphanie Buisine, sbuisine@cesi.fr, CESI, LINEACT, Nanterre, France.

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focusing on final performance, evaluating efficiency, productivity, or synergy. Thereby, they often overlook the resources and the process that led to the outcome and neglect the underlying mechanisms that drove its emergence. Among those, collective functioning can be dramatically influenced by, e.g., group composition, task structure, leadership, and affective states [17, 29, 34]. In this paper, we will put a special emphasis on group interaction, in particular nonverbal communication, because we see it as the manifestation of an integrative process through which group potential can unfold and develop over time. Previous work seldom adopts a fully interaction-centered view of collective intelligence that examines how individuals organize, interact and coordinate over time, and it largely overlooks the nonverbal layer of interaction (e.g., gaze, posture, vocal prosody) that silently orchestrates action and signals the group's social and cognitive state [30]. As a result, we still lack a coherent framework that explains when and why interaction dynamics translate into enduring collective intelligence.

This is the context in which our contribution is situated. We argue that a dynamic theoretical model is necessary for developing hypotheses on improving collective intelligence, aligning with the overarching question of "how to enhance collective intelligence." Our approach is specifically interaction-centered, emphasizing communication and, more importantly, nonverbal cues. Moreover, we highlight the behavioral dimension as a key driver for fostering coordination, cohesion, and, ultimately, collective performance. Additionally, we incorporate the macro-level temporal aspect as an analytical lens to understand how a team learns, adapts, and builds intelligence through interactions. Building on cumulative findings from the team's literature to understand how outcomes emerge at the collective level, we focus here on small to medium-sized work groups that collaborate face-to-face or through rich synchronous media. Thus, large-scale crowdsourcing collectives fall outside the scope of this paper.

Our objectives are therefore intertwined rather than separate. First, we integrate existing collective intelligence models into a single framework that goes beyond outcome assessment to reveal the behavioral mechanisms at work. Second, within this framework, we argue that nonverbal cues simultaneously operate as channels of coordination and diagnostics of the collective's emergent state. Third, we wish to emphasize that the temporal aspect, considered at the macro level, can reshape internal dynamics and prove decisive in establishing robust collective intelligence over the long term.

Practically, unifying these theoretical strands yields an explanatory scaffold that enriches scientific understanding while guiding concrete interventions. For instance, sensor-based monitoring of nonverbal synchrony and facilitation techniques that deliberately modulate the rhythm of exchanges could be deployed in real time to boost collective intelligence as it unfolds. In this way, the present article lays the groundwork for a framework that not only deepens our grasp of collective intelligence but also offers actionable drivers for cultivating it.

2 Background

In this section, we first present various theoretical perspectives on collective intelligence that have shaped our current understanding of teamwork, then introduce the Inputs–Mediators–Outputs–Inputs (IMOI) model [29] as groundwork for a unifying framework for studying team behavior. In what follows, we use the terms "team" and "group" interchangeably, recognizing that a team is a special kind of group but that general group characteristics (task structure, member interaction) equally apply to teams [29, 46].

2.1 Perspectives on Collective Intelligence

In what follows, we briefly introduce three central perspectives on collective intelligence. First, we adopt Woolley's [60] definition of collective intelligence as "a group's general ability to accomplish a wide variety of tasks." Next, we rely on the Transactive Systems Model of Collective Intelligence [23] for a detailed account of how team cognition emerges in real time, emphasizing the dynamic coordination of memory, attention, and reasoning. We adopt TSM-CI because it is the only framework that explains team cognition dynamically, capturing how memory, attention, and reasoning co-regulate over time rather than relying on static snapshots. This unique perspective makes it the ideal choice for our analysis of collective intelligence. Finally, we turn to the notion of synergy to show how a team's collective output can exceed the sum of its individual contributions. Each of these views helps to clarify different aspects of how collective intelligence develops and operates, as discussed below.

2.1.1 Collective Intelligence as a Capacity. In 2010, Woolley and colleagues [60] introduced the idea of a collective intelligence factor, the "C-factor," which they likened to Spearman's g-factor for individual intelligence [55]. Their protocol involved submitting various groups to a broad range of tasks meant to reflect multiple dimensions of collective performance, based on McGrath's circumplex [43]. The results from these tasks were aggregated to produce a single global performance score. Through factor analysis, Woolley and colleagues observed that a single factor, the C-factor, accounted for about 43% of the variance in group performance, a finding similar to the explanatory power of the g-factor in individual psychometric tests. Building on this seminal contribution, subsequent work has examined predictors that can be organized into three broad families: (1) composition-based attributes, (2) effort–strategy alignment, and (3) interaction-quality indicators.

Composition captures who the members are and what their traits or characteristics are. The original study [60] already showed that a group's average or maximum intelligence ($r = 0.15$ and $r = 0.19$), measured by the Wonderlic Personnel Test of Individual intelligence, showed only a weak link with collective intelligence, whereas social sensitivity, which is the ability to accurately understand the emotions of other people and react accordingly, as measured by the "Reading the Mind in the Eyes" test [3], was a far more robust predictor ($r = 0.58$). A higher proportion of women in the group, coupled with high social sensitivity scores, also contributed to the C-factor. These findings proved robust across different cultural contexts and modes of interaction (face-to-face or online platforms) [14, 15, 32]. In addition, structural features such as hierarchy depth and diversity profiles (cognitive, ethnic) likewise fall into this family and have been linked to collective intelligence [1, 2, 8, 57].

Turning to effort–strategy alignment, concerning how well resources and plans fit task requirements. A recent a meta-analysis [53] of studies using the C-factor identified three major predictors of the C-factor: collective effort (i.e., the total individual effort expended across all tasks), the appropriate use of skills (the group's ability to align members' skills and contributions with the task requirements), and strategy (the use of a strategy well suited to task execution).

Finally, interaction quality focuses on how members communicate (e.g., turn-taking patterns, vocal/prosodic synchrony, feedback signals), highlighting that the dynamics of exchange can be as important as composition [57, 60]. This dynamic particularly depends on the effective integration of individual expertise [35], balanced communication among participants, also considered as an important predictor of the C-factor ($r = 0.53$) [60], and the adaptation of collaborative processes to environmental constraints [53]. Most studies operationalize this layer through verbal traces, leaving open the role of nonverbal channels and their evolution over time.

To synthesize these findings, Woolley and colleagues proposed a two-level distinction between bottom-up factors (team characteristics and contextual inputs such as initial composition or available resources) and top-down factors (collaborative processes and emergent states arising directly from interaction) [59]. In their work, this dichotomy is sketched for organizing explanatory variables but remains underexploited for theoretical or design purposes. By contrast, the present paper places that distinction at center stage to understand more deeply how dynamic, interaction-driven top-down mechanisms continuously interplay with and reshape bottom-up inputs.

2.1.2 Collective Intelligence as Emergent State. The Transactive Systems Model of Collective Intelligence (TSM-CI), proposed by Gupta and colleagues [23], suggests that much like a human brain or a technological device, a team functions as an intelligent system with three core components: memory, attention, and reasoning [40]. Each of these functions is fulfilled within the team by a distinct transactional subsystem: the Transactive Memory System, the Transactive Attention System, and the Transactive Reasoning System. According to this perspective, collective intelligence emerges when there is a structural isomorphism, an effective coordination, among these three subsystems, allowing the group's overall performance to surpass the sum of individual cognitions [23].

The Transactive Memory System (TMS) reflects members' ability to continuously identify and update "who knows what" in the team [52]. It relies on collaborative, so-called "transactional", exchanges that ensure the specialization and distribution of knowledge [38]. The Transactive Attention System (TAS) [23] centers on the coordination of limited attention: setting priorities, signaling availability, and distributing workload according to urgent situations [8, 15]. Finally, the Transactive Reasoning System (TRS) [16] manages cohesion and adherence to common objectives, relying on ongoing negotiation of priorities and integration of individual and collective interests [39]. In TSM-CI, each subsystem includes iterative loops (updating, allocation, and retrieval) through which members adjust their actions and mental representations in response to task changes and their environment.

One key strength of TSM-CI is its explicit consideration of dynamic diagnostic indicators for these transactional subsystems. For instance, specific collaborative processes, such as collective effort, the appropriateness of strategies, and effective use of knowledge and skills, serve as real-time measures reflecting the underlying functioning of TMS, TAS, and TRS [24, 53]. Variations in collective effort may signal weaknesses in TRS retrieval processes, such as decreasing motivation or engagement. Likewise, persistent reliance on inadequate performance strategies can indicate ineffective TAS allocation and retrieval processes, while consistent misapplication of group knowledge suggests deficits in TMS management [22]. Monitoring these indicators can thus pinpoint areas requiring intervention, offering the team practical opportunities for enhancing collective performance.

Additionally, the TSM-CI builds on two inherent functions that ensure the system operates smoothly. When these three transactional subsystems cooperate harmoniously, the collective is able, on the one hand, to use its cognitive resources effectively (the efficiency function), and, on the other, to maintain sufficient levels of trust and engagement (the maintenance function) [24]. For example, the TMS guarantees that information circulates to the right people, TAS makes sure attentional capacity is managed without excessive dispersion, and TRS aligns objectives and manages individual motivation over time. This combined orchestration gives the team the flexibility to adapt to dynamic or uncertain environments and fosters the emergence of collective intelligence.

2.1.3 Collective Intelligence as a Performance Gain. In a collective context, the performance gain can be explained through synergy, which refers to a group's ability to achieve an outcome exceeding the simple sum of individual contributions [26]. This emerging collective performance is based on the coordination of efforts, the integration of knowledge, and the optimization of interactions among team members. The literature [30] distinguishes two main forms: weak synergy, in which collective performance surpasses the average individual performance but does not exceed the best individual performance [26, 37] and strong synergy, where the group manages to outperform even its highest individual performer [7]. The emergence of synergy relies heavily on the quality of member interactions and on the collective decision-making rules governing those exchanges [10, 11]. Thus, majority vote or collective consensus decisions influence how collective intelligence is mobilized and optimized [58]. From this perspective, a team achieves strong synergy when member interactions generate a cognitive surplus, that is, a collective capacity that goes beyond what individuals could have produced on their own [44].

However, synergy does not automatically arise as soon as a collective is formed: it strongly depends on the interaction and coordination mechanisms structuring the team [18]. The lack of such dynamics can even produce adverse effects, such as social loafing or the dominance of a subgroup, hindering the emergence of optimal collective intelligence [20, 27]. Thus, synergy does not stem merely from the aggregation of individual skills. Rather, it resides in the effective sharing and integration of these skills via interactive and organizational processes that allow the team to achieve a level of performance greater than that of its individual members acting alone [35, 53].

2.2 An Integrative Approach: The IMOI Model

In an effort to describe the overall functioning of a team working toward a common goal, Ilgen and colleagues [29] propose the theoretical IMOI framework, which extends the Input–Process–Output model introduced by McGrath [43]. The authors introduce the notion of emergent states to more accurately capture group phenomena that cannot be reduced to mere processes. This shift reflects the iterative and recurrent dynamics of teamwork, in which Outputs, in turn, become new Inputs over successive cycles. Such an approach underscores the need to consider multiple feedback loops within the system rather than confining analysis to a simple linear transformation of initial resources into final performance [47].

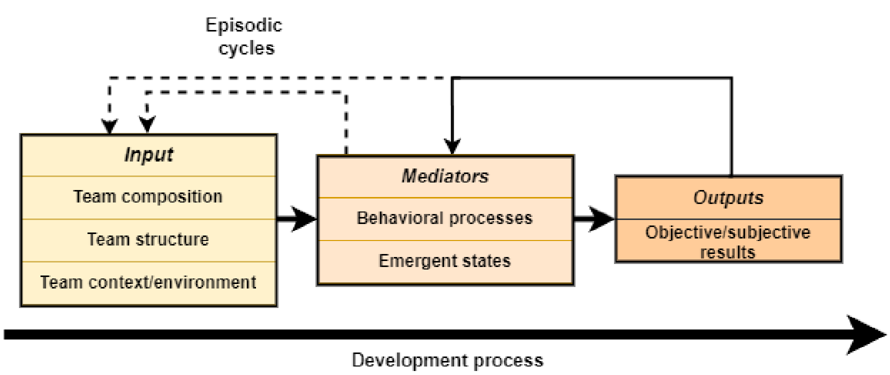

Fig. 1. **IMOI Model [29]**
Input refers to the team's initial conditions (composition, structure, environment). *Mediators* comprise both behavioral processes and emergent states shaping how the team transforms inputs into outcomes. *Outputs* include objective and subjective results (e.g., performance, satisfaction) that can feed back into new input cycles.

Within this model, illustrated in Figure 1, Inputs represent the initial characteristics of team members, tasks, and contexts in which they operate. These Inputs play a significant role in how a team functions. For instance, personality traits, skills, preferences for teamwork, along with knowledge, abilities, and other attributes, significantly influence team performance [2, 17, 60]. This component also accounts for team composition in terms of visible diversity (age, gender, background) and deep diversity (attitudes, goals), as well as available resources, organizational culture, and the work environment. Finally, the complexity and nature of the task are critical Inputs. Well-defined, structured tasks, for example, may facilitate coordination and communication within the team [17]. In IMOI terms, these features represent bottom-up factors that set the stage for higher-order phenomena.

Mediators encompass both behavioral processes (planning, coordination, decision-making) and emergent states, as cognitive or affective constructs that develop over a team's lifespan and shape its outcomes. Unlike behavioral processes, these states (e.g., trust, cohesion, shared attitudes) arise from members' ongoing interactions and, once formed, exert a reciprocal influence on the team's subsequent performance and viability [29]. Among these emergent states, team cognition and shared mental models [6, 9] highlight the formation of a collective schema that fosters anticipation and implicit coordination among members [12, 13]. The knowledge thus shared may concern the task (resources, strategies) or the team itself (expertise, roles). One example of such a mediator is the Transactive Memory System (TMS), which underscores how expertise is distributed and specialized over time [45], thereby contributing to the broader cognitive landscape that shapes how team members coordinate their efforts. This component also includes concrete mechanisms, or processes, such as communication and cohesion management [41]. In this regard, cognition can be "shared" (overlapping knowledge among individuals) or "complementary" (the aggregation of distinct expertise), two configurations capable of influencing performance depending on whether they pertain to the task or to interpersonal coordination [12, 13, 50]. Thus, mediators represent top-down mechanisms that can amplify or mitigate the impact of initial inputs.

All these factors direct the Outputs, which refer to the results achieved (quality, efficiency, creativity, satisfaction, or learning). These can be evaluated based on objective (productivity, profitability) or subjective (members' perceived well-being) criteria [36]. The performance thus attained subsequently feeds back into future cycles and can influence team composition, the setting of new priorities, or resource allocation [42]. This dynamic perspective, inherent in the IMOI model, underscores the evolutionary and adaptive character of collective functioning by highlighting the way teams learn from their own results to optimize themselves over time [25]. These outputs, therefore, form a natural bridge to the performance-gain perspective developed in the previous subsection.

Taken together, IMOI clarifies when capacity factors matter (Input stage), how emergent cognitive-affective states form and operate (Mediator stage), and why specific interaction patterns convert those states into strong synergy (Output stage). This integrative view, summarized in Figure 2, sets the foundations for the next section, in which we examine collective intelligence explicitly as a temporal, interaction-centered phenomenon and highlight the central role of nonverbal dynamics.

3 Collective Intelligence as an Interactional and Temporal Process: Needs and Challenges

3.1 Addressing Conceptual and Methodological Limitations

While various theoretical approaches (i.e., IMOI [29], TSM-CI [23], C-factor [60], and synergy models [10, 26, 37]) have significantly advanced our understanding of collective intelligence, current literature often presents these perspectives independently, resulting in a fragmented conceptual landscape. Each model has distinct strengths: IMOI highlights feedback loops and emergent states [29], the TSM-CI emphasizes cognitive subsystems and their dynamic interactions [23], the C-factor approach provides robust indicators of a group's baseline performance capability [53, 60], and synergy models elucidate how collaborative interactions yield performance beyond individual capacities [7, 37]. Yet, there remains an evident gap in unifying these distinct dimensions and particularly when it comes to integrating the temporal dimension, socio-cognitive processes, and performance outcomes under a single coherent theoretical lens

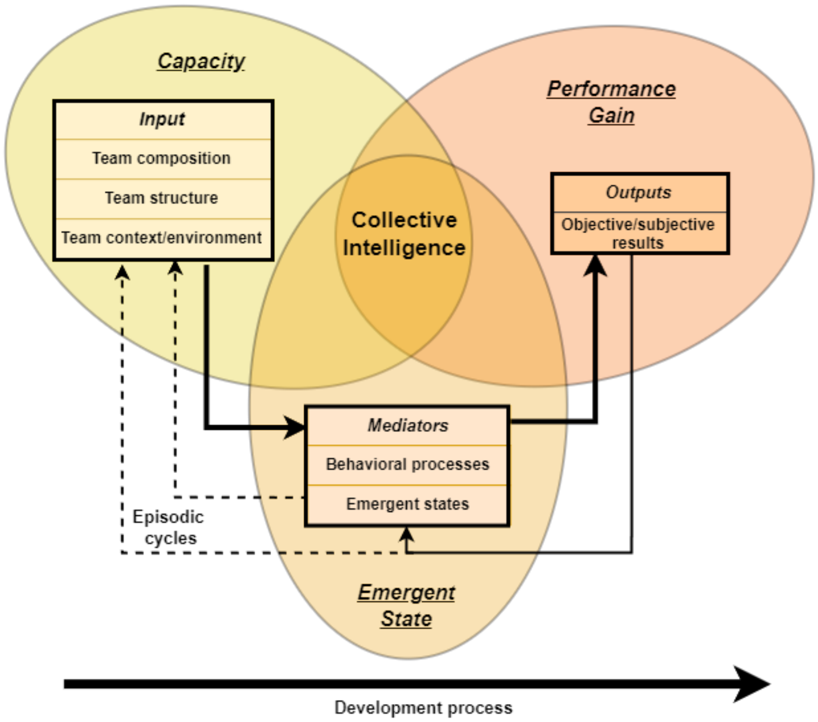

Fig. 2. **Mapping the three CI perspectives onto the IMOI cycle.**
The Venn diagram situates **Capacity** studies on the *Input* side (team composition, structure, and context), **Emergent-State** research on the *Mediator* layer (behavioral processes and emergent states), and **Performance Gain** work on the *Output* side (objective/subjective results). The intersection highlights collective Intelligence as an ongoing accomplishment that emerges where these three perspectives overlap.

[30]. Developing an integrative model would represent a critical step toward a better understanding of how collective intelligence develops, evolves, and can be systematically fostered over time.

Beyond conceptual fragmentation, the empirical study of collective intelligence faces considerable methodological challenges. First, longitudinal data collection is notoriously complex: tracking teams over extended periods requires substantial resources and raises issues related to participants' retention and experimental consistency [20, 25]. Observing nonverbal behaviors systematically adds another layer of difficulty due to their inherently subtle and rapid nature [5, 31, 56]. Precise coding of nonverbal cues demands robust frameworks and reliable raters—requirements that increase time and financial costs significantly [33, 54]. Additionally, clearly isolating and measuring the unique contributions of each cognitive subsystem (TMS, TAS, TRS) remains challenging, as these subsystems interact in highly interdependent ways, often obscuring direct causal relationships [22]. As a result, there is a notable shortage of detailed longitudinal studies, limiting our ability to draw conclusions about how collective intelligence emerges, stabilizes, or declines in various contexts [25, 30].

In short, these conceptual and methodological limitations underscore the necessity for a comprehensive, integrative approach that merges insights from diverse theoretical models. Addressing these limitations calls for interdisciplinary collaboration (i.e., integrating expertise from psychology, management, computer science, and engineering) to develop and validate unified frameworks that capture collective intelligence's inherent complexity [21]. Furthermore, promoting long-term field studies and rigorously designed experiments becomes essential to empirically validate theoretical constructs. Such research, enriched by technological advancements, can provide concrete insights and actionable guidance on fostering robust and adaptive collective intelligence in real-world teams.

3.2 Recognizing the Importance of Temporality and Nonverbal Interaction

Building on the gaps outlined in the previous subsection, we contend that collective intelligence research must pay simultaneous attention to how teams evolve across successive feedback cycles and how nonverbal interaction cues govern that evolution. Global metrics such as the C-factor [60] offer a useful baseline, yet they conceal the long-range trajectory through which shared knowledge, coordination routines, and collective goals are progressively refined [19, 53]. Teams learn iteratively: outputs at one moment become inputs for the next, and high initial potential can fade if mental models are not updated, whereas modest teams frequently surge once they institutionalise expertise sharing or attention re-allocation [29]. We know that high initial potential does not necessarily guarantee optimal performance if the group fails to adapt over time [23]. Conversely, teams with modest beginnings may substantially improve once they establish routines for allocating attention or distributing expertise. Tracing this macro-temporal arc, therefore, demands repeated observation of how roles are re-negotiated, resources re-aligned, and objectives recalibrated.

Beyond temporal progression, collective intelligence also hinges on how members actively co-construct their activities [27, 51]. Nonverbal signals, such as gestures, body orientation, or interpersonal distance, have proven to be particularly revealing. They offer insights into trust, cohesion, and the fluidity of coordination [5, 31]. For instance, in their work, Biancardi and colleagues [5] focuses on the TMS underscore that "credibility" can be inferred from low speaking-turn frequencies and minimal physical movement, whereas "coordination" becomes apparent when team members sustain longer, uninterrupted exchanges and remain close enough to each other for spontaneous interaction. In parallel, multimodal approaches that combine analyses of speech (interruptions, lexical alignment) with behavioral or psychological markers (dominance, shared attentional focus) highlight the depth of these collaborative processes [33, 56]. Such findings point to the interplay of micro-behaviors as a key driver of how the team collectively learns, adapts, and ultimately performs. Simply put, nonverbal communication channels the team's collective synchronization, enabling members to keep track of "who knows what" or to quickly sense evolving priorities [4, 25, 28]. By focusing on these micro-level processes, researchers can better grasp how collaboration remains flexible and responsive to changing demands.

Taken together, the emphasis on macro-level temporality and on the real-time, collaborative processes that underpin collective intelligence highlights why static or solely outcome-based evaluations prove insufficient. Teams need time to experiment, form stable patterns of attention, and build shared mental models. At the same time, micro-behaviors such as speaking turns, posture, and interpersonal distance actively shape the group's cohesion and performance capacity. Thus, integrating macro-temporal trajectories with these micro-level signals closes the conceptual gap between capacity-based, emergent-state, and performance-gain perspectives. Longitudinal patterns reveal whether latent capacities crystallize into durable performance, while real-time cues partly reveal and make visible those mechanisms. Next section elaborates on a unified framework that weaves these dimensions into the IMOI architecture, thereby addressing the fragmentation highlighted earlier.

4 A Unified Framework for Collective Intelligence

Building on the findings discussed earlier, we propose an integrative theoretical framework, illustrated in Figure 3, that aims to overcome the limitations identified in the literature, particularly the lack of systematic consideration of nonverbal communication and temporal dynamics already embedded in the IMOI cycle. Rather than redefining collective intelligence, the framework links together the major approaches that have shaped its study within a single scaffold grounded in IMOI's Inputs, Mediators, Outputs, and feedback loops. The subsections below detail each framework component and explain how they address critiques of existing models regarding interaction and temporality.

4.1 Model Components

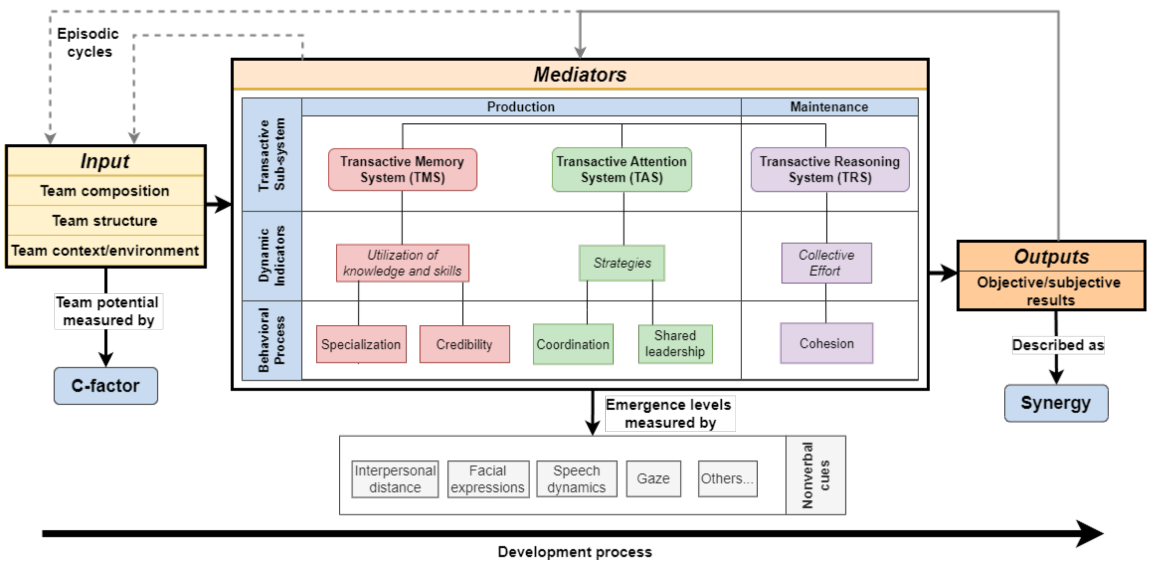

Fig. 3. **Unified Model of Collective Intelligence**
Inputs refer to the team's initial conditions: composition, structure, and environment. The C-factor estimates the team's baseline potential. *Mediators* capture interaction processes via three subsystems (TMS, TAS, TRS) and their associated indicators. TMS handles knowledge distribution, TAS manages attention, and TRS aligns goals and maintains motivation. Behavioral processes (e.g., specialization, credibility, coordination, shared leadership) and nonverbal cues (e.g., gaze, distance, gestures) provide real-time data on how efficiently these subsystems function. *Outputs* represent the team's results, both objective (performance) and subjective (cohesion, satisfaction), and can reflect synergy that exceeds the sum of individual efforts.

4.1.1 *Inputs.*

This component, like in the original IMOI model, encompasses the team's initial configuration (diversity, skills, personality traits), the broader context (resources, organizational culture), and the nature of the task (structure, complexity, uncertainty). Here, the concept of potential comes into play, illustrated in particular by the C-factor, presented in the literature as an indicator of a group's general capacity to perform a broad range of tasks [60]. A high C-factor can be seen as a starting indicator of the team's "collective capital", meaning the level of aggregated cognitive, social, and interactional capacities. However, as emphasized by Graf-Drasch et al. [20], possessing strong potential from the outset does not guarantee that a group will automatically capitalize on it. Coordination mechanisms, cohesion, and goal alignment must then be enacted through interactional processes (Mediators) to transform this potential into actual performance. Thus, the C-factor serves as a starting estimate: it indicates the group's readiness to manage diverse tasks, but by itself, does not ensure the emergence of lasting collective intelligence. Teams still need to activate and develop their capacities through the processes described in the Mediators. In other words, Inputs provide the raw material—cognitive resources, contextual supports, and initial motivation—that must be channeled into coherent collaborative action if the group is to realize sustained collective intelligence.

4.1.2 Mediators. At the heart of our proposed model, the Mediator component represents the space where interaction truly unfolds as the team works together on a task. The three transactional subsystems of TSM-CI describe how information is shared (TMS), collective attention is regulated (TAS), and common goals are aligned (TRS). These processes are complemented by cooperative mechanisms (e.g., coordination, cohesion, conflict management, shared leadership) that manifest in both verbal and nonverbal exchanges [22]. Nonverbal cues thus play a dual role: they serve as indicators of interaction quality (e.g., turn-taking, spatial usage, mutual trust) and as facilitators of synchronization (e.g., implicit adjustments of gestures or gaze). Here, we focus on nonverbal cues because they (a) silently orchestrate synchrony and coordination and (b) can now be collected unobtrusively via depth cameras, lightweight wearables, or audio-based turn-taking trackers, making field deployment feasible in most modern workplaces in real time [49].

Within this component, the TSM-CI model specifies two main functions that a complex system, such as a team, must fulfill: the production function (or efficiency), which mobilizes transactional subsystems to accomplish the task, and the maintenance function, important for sustaining cohesion, engagement, and the trust needed to maintain the group over time. For example, Biancardi et al. [5] show that a coherent distribution of speaking turns and a low frequency of movement strengthen TMS credibility. As for TAS, signs of effective coordination (synchronized gestures, fluid eye contact, few interruptions) demonstrate well-regulated collective attention [4, 48]. Finally, TRS draws on cohesion fostered by physical proximity or frequent eye contact, which supports affective regulation and collective decision-making [28, 31].

Observing the emergence and effectiveness of these subsystems through changes in nonverbal cues would allow to move beyond a static view of collective intelligence. We recognize that TMS, TAS, and TRS develop progressively over multiple interactions and feedback loops. These repeated adjustments, whereby the team refines its members' specializations, attention management, and sense of belonging, reveal an "in-progress" collective intelligence. Behavioral signals are significant for diagnosing coordination and cohesion levels, indicating a group's growing capacity to tackle increasingly complex tasks. As described in the previous section, the TSM-CI model highlights the importance of specific collaborative processes, such as collective effort, performance strategies, and utilization of knowledge and skills, as dynamic indicators capable of diagnosing and regulating the transactional subsystems in real-time. For instance, fluctuations in collective effort can indicate deficiencies in TRS retrieval processes, while inappropriate or inefficient use of knowledge and skills may suggest issues in TMS allocation and retrieval. Thus, monitoring these collaborative processes through measures proposed by Riedl et al. [53] allows teams to proactively identify areas needing intervention, improving collective effectiveness. TSM-CI, coupled with nonverbal and collaborative-process analyses, therefore illustrates how collective intelligence is continuously co-constructed: each member adapts their involvement, gestures, and strategies over successive sessions, driving the collective toward higher and more sustainable performance.

4.1.3 Outputs. These are the tangible outcomes of collaboration [29], whether in terms of immediate performance (quantitative or qualitative), team satisfaction, or group learning. They also include the collective's ability to develop, over the longer term, a synergy that goes beyond the sum of individual contributions [10, 37]. In other words, beyond operational effectiveness, the focus is on indicators revealing the team's potential to exceed its best individual performance (strong synergy) or to maintain a high level of cohesion and well-being.

Within the IMOI framework, these results act as new Inputs in subsequent cycles: success can reinforce role distribution or mutual trust, while failure may prompt a reassessment of the team's composition or its modes of interaction. This feedback effect underscores the importance of monitoring not only performance but also the quality of interactions and the team's trajectory, in order to determine whether the group can continue to grow and develop genuine collective intelligence over time. Moreover, the temporal dimension of the model suggests that the group gradually builds its collective intelligence through repeated cycles, continuously adjusting the TMS, TAS, and TRS subsystems [23].

4.2 The Role of Interaction and Temporality in Collective Intelligence

Our proposed model directly addresses critical limitations identified in prior literature, specifically the insufficient attention given to interaction processes and temporal dynamics [30]. Previous studies have frequently emphasized final performance metrics [10, 37, 60] or pre-existing group capabilities [1, 8, 53], thereby overlooking the nuanced ways teams organize, communicate, and adapt over time [29]. To address this gap, our model explicitly integrates how teams interact and coordinate their efforts across multiple collaborative episodes, making the temporal grain of analysis explicit: interaction is traced episode by episode, and the pattern of change itself becomes an explanatory variable.

We have retained the IMOI scaffold, enriched it with the transactional subsystems of TSM-CI, and placed non-verbal cues at the centre of analysis while drawing on other collective intelligence perspectives. This choice relies on the fact that research on small groups shows that nonverbal cues (a) convey socio-emotional and cognitive information that speech often obscures; (b) appear earlier than verbal statements when coordination falters or improves; and (c) are less susceptible to impression management [49]. Because these signals are continuous, they provide a high-resolution, real-time view of team functioning [4, 28, 31]. Tracking them as time-ordered markers for TMS, TAS and TRS enables the framework to answer long-standing critiques that earlier models pay too little attention to interaction processes and temporality.

Additionally, our model treats temporality on two interwoven levels. At the macro level, teams progress through successive cycles of trial-and-error, experimentation, learning, and refinement, echoing the importance of repeated interaction stressed by Janssens and colleagues [30]. Longitudinal observation of these feedback loops is therefore crucial for explaining how collective intelligence takes shape and stabilizes in real-world settings. At the micro level, millisecond-scale shifts in gaze, posture, or interpersonal distance serve as early warning signals that a new cycle is about to begin—signals that can power real-time diagnostics or adaptive interventions.

In sum, by placing the dynamics of interaction and temporal progression at the heart of our framework, this integrative model addresses existing theoretical limitations, providing a practical basis for analyzing and ultimately enhancing collective intelligence over time. By embedding these temporal layers and nonverbal diagnostics at the core of the framework, we move beyond static inventories of inputs and outcomes. The result is a practical platform for tracing, explaining, and ultimately steering the developmental trajectory of collective intelligence in everyday teams.

5 General Discussion

Our proposed integrative framework combines several influential perspectives on collective intelligence to provide a more comprehensive and dynamic understanding of collective intelligence. A core strength of this integration is that it directly addresses the critiques raised by Janssens et al. [30], emphasizing the importance of viewing collective intelligence as a process rather than solely as an outcome. In doing so, our model highlights that collective intelligence does not simply emerge from a fixed state or single snapshot, but is built and reshaped continuously over multiple cycles (e.g., work sessions, successive projects).

This emphasis on interaction processes and temporality is necessary because it recognizes that internal dynamics, such as communication regulation through nonverbal exchange, the alignment of goals, or the distribution of attention, play an essential role in team performance. For instance, subtle nonverbal signals significantly influence how effectively teams coordinate and collaborate, reinforcing collective cognitive systems like the TMS, TAS, and TRS. Such a detailed distinction among TSM-CI components ensures that collective intelligence is not merely seen as a simple aggregation of individual competencies but rather as the ongoing management of specialized knowledge, shared attention (TAS), and aligned goals and motivations (TRS) within the team. This allows the framework to directly address critiques regarding the overly outcome-focused nature of traditional collective intelligence research, advocating instead a deeper, more dynamic exploration of team behavior as it unfolds. This focus moves research beyond outcome-centric views and grounds it in the day-to-day behavior of small to medium sized synchronous workgroups.

Moreover, the framework invites a theoretical shift from trait-based accounts to a relational, systems-oriented view of collective intelligence. By specifying how constructs such as cohesion, speech turn dynamics, psychological safety and prosodic synchrony interact within and across IMOI cycles, it reframes collective intelligence not as the sum of static variables but as an emergent property of coupled feedback loops. This perspective encourages researchers to (1) model leading and lagging relations among constructs; (2) to test nonlinear effects such as threshold levels of TAS required before gains in TMS translate into performance; and (3) to apply time series techniques drawn from dynamical systems theory. Pursuing this agenda moves the field from cataloging correlations to explaining mechanisms, clarifying why certain interaction patterns convert latent capacity into strong synergy and when interventions should focus on specific subsystems to maximize collective gains.

A promising methodological direction emerging from our framework is the precise observation and measurement of nonverbal cues within teams. Techniques such as video recording, automated behavioral coding, gaze tracking, and interpersonal distance measurement allow researchers to quantify subtle interactional phenomena (e.g., micro-coordination or gesture synchronization) that have previously been understudied in collective intelligence research. This attention to nonverbal behaviors is particularly useful for investigating implicit indicators of trust, cohesion, and collective coordination, that verbal transcripts miss, thereby offering insights into team dynamics beyond traditional verbal or outcome-focused measures.

Moreover, multi-user immersive Virtual Reality (VR) adds a valuable dimension for investigating these interactional processes in real-time group settings. In such VR environments, multiple participants can collaboratively perform tasks while sensors automatically capture gaze direction, gestures, interpersonal distance, facial expressions, and vocal dynamics with high precision. Researchers can also systematically manipulate task parameters, spatial configurations, and role distributions, making it possible to observe, in detail, how teams adapt and respond to varying conditions. This controlled yet immersive setup highlights how group members interact, synchronize their nonverbal signals, and ultimately develop or refine their collective intelligence over successive sessions. Although VR set-ups remain resource-intensive, their ability to combine ecological validity with experimental control makes them a powerful testbed for theory-driven interventions.

The longitudinal aspect embedded in our framework represents another significant methodological strength. By observing the same team over multiple sessions or an extended period, researchers can identify how interactional patterns evolve, thus capturing both the growth and potential stagnation of collective intelligence. Such longitudinal studies enable the detection of critical turning points—such as changes in leadership style, role adjustments, or shifts in communication patterns—and provide valuable insights into how nonverbal behaviors adapt over time, ultimately shaping the team's trajectory towards sustained collective intelligence.

Despite its integrative strengths, the framework presented in this article reveals several areas where future research is necessary. Firstly, the relative contribution and weighting of each TSM-CI subsystem (TMS, TAS, TRS) to overall collective intelligence remains unclear. For instance, it is not yet understood to what extent a highly developed TMS (i.e., efficient knowledge distribution and updating) can compensate for a weak TAS (management and regulation of collective attention), or whether optimal team performance requires all three subsystems to be simultaneously developed to a certain degree [23]. Clarifying these interdependencies would significantly refine our theoretical model and provide practical guidelines for enhancing collective intelligence. Thus, a necessary next step is to conduct a systematic inventory of existing studies that maps how the constructs in our model relate, for example, cohesion and turn-taking dynamics, so we can identify overlooked pairings, clarify these interdependencies, and thereby both sharpen the framework and generate practical guidelines for strengthening collective intelligence.

Secondly, the systematic and accurate coding of nonverbal behaviors remains methodologically challenging. The causal connection between these nonverbal indicators and team performance is not yet fully established, partially due to the subtle influence of contextual factors, such as task type, complexity, or stress levels [5, 25]. Moreover, rigorous empirical validation is required to understand the relation between these nonverbal cues and each specific subsystem within the TSM-CI framework. Future research should focus on refining methodologies—combining observational coding, automated systems (e.g., computer vision or sensor technologies), and sophisticated statistical modeling—to accurately investigate these intricate links.

Thirdly, a significant gap exists in the availability of longitudinal data, not only within collective intelligence research but broadly in group dynamics studies. While the theoretical importance of observing team evolution over extended periods (covering multiple sessions or projects) is widely acknowledged, few empirical studies have successfully implemented this approach [30]. As a consequence, our current understanding of how teams evolve—whether progressing towards greater collective intelligence, stagnating, or declining—is limited by a scarcity of detailed empirical trajectories. Thus, future studies should emphasize longitudinal designs, field studies, or controlled experimental setups that capture continuous observational data. Such efforts would substantially enrich our understanding of the complex developmental dynamics underlying collective intelligence in teams.

6 Conclusion

In this paper, we proposed an integrative theoretical framework emphasizing the behavioral processes, particularly interaction dynamics and nonverbal communication, along with the critical role of temporality in the emergence of collective intelligence. By explicitly integrating nonverbal behavior as a central element in team regulation and coordination, this framework directly addresses the limitations inherent in result-centered approaches that dominate existing research.

This unified model provides a broader perspective of collective intelligence, shifting the focus from final performance alone to the explication of team self-organization, regulation, and adaptation over time through interactions. Specifically, the emphasis on nonverbal cues allows for a deeper understanding of team dynamics by examining subtle behaviors and implicit signals that shape collaboration, coordination, and team cohesion.

Beyond this theoretical synthesis, several avenues for future research are proposed. First, there is a clear need for longitudinal studies. Capturing the progressive development of collective intelligence from a behavioral perspective requires observing teams over multiple sessions to understand the gradual adjustments in their transactional subsystems. Second, developing reliable measurement tools for nonverbal cues emerges as a promising methodological avenue to deepen our understanding of collective intelligence dynamics and to design interventions fostering its growth. Finally, further interdisciplinary collaboration between psychology, computer science, management, and computational fields is crucial to address these challenges and fully realize the practical potential of the proposed integrative framework.

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