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# Interpersonal factors that contribute to collective intelligence in small groups a qualitative systematic review

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**Abstract**
The study of collective intelligence has focused in the last years on crowdsourcing and artificial swarm intelligence. Currently, large online communities have demonstrated their effectiveness but even if the contributions in this domain are significant, it remains essential to question the functioning of collective intelligence in small groups, especially since the gain in popularity of brainstorming strategies, focus groups and co-working practices. In this context, we conducted a qualitative systematic review using Prospero, PRISMA protocol and bias assessment to identify the factors currently recognised as impacting on the emergence of collective intelligence in small groups. These factors were then organised according to the different levels of abstraction observed in research about collective intelligence. From this work, collective intelligence appears as the crystallization of emerging properties that manifest themselves in interactions and whose possibility of existing is intrinsically linked to meta-cognition and meta-communication processes.

**Keywords** Collective intelligence · Small groups · Interpersonal · Interaction · Systematic review

## 1 Introduction

Collective Intelligence (CI) - when applied to a group's performance – can be defined as "an intelligence distributed everywhere, constantly valued, coordinated in real time, which results in an effective mobilization of skills" (Levy, p.14, 1997). This definition encapsulates various phenomena such as the *emergence of a shared vision*

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(Simon, 1969; Courbon, 1979 ; Goux-Baudiment, 2001), *the co-construction and collective use of this shared vision* (Mack, 2004; Rogalski, 2005), *the pooling, the organization and the accessibility of intelligences and information* (Glynn, 1996 ; Besson, 2002), *an optimal mobilization of skills, resources and conditions needed to progress* (Rabasse, 1997 ; Zara, 2004 ; Meunier, 2013) as well as *a better performance in problem-solving and decision-making* (Bonabeau, 1994 ; Garnier, 2001 ; Penaleva, 2004) (Zaïbet, 2007). In practice, CI is generally mobilized in brainstorming activities, focus groups, collaborative online encyclopaedias, data prediction, ad hoc commission and scientific forums.

Since the discovery of the wisdom of crowds effect, defined as "the capacity of groups to perform more efficient evaluations and predictions than experts or isolated individuals through mutual correction of bias" (Surowiecki 2004), most of research on collective intelligence have focused on large online communities engaged in crowdsourcing activities." (Nguyen et al. 2019a). These research mainly consider CI as a statistical phenomenon, which consequently does not provides an in-depth understanding of the underlined CI mechanisms and processes, while simultaneously neglecting to offer a "sufficient explanatory theory" for collective intelligence (Bonabeau 2009; Luo et al. 2009; Schut 2010; Salminen 2012). In particular, the research polarization on CI as a statistical phenomenon lead to the use of a reductionist aforementioned definitions of CI as these definitions mention the role of intelligence and information without discussing the role of emotion known to be an essential part of human interactions. In addition, these definitions mention the notion of groups and collectives without offering more precision on group size, dynamics and context). Furthermore, it is worthy to note that despite a common use of the term "interaction" in relevant author's publications, the concept of interaction is rarely based on a formalised definition as well as being poorly studied. This reinforce the common idea that interactions are the "black box" of Collective Intelligence.

It is possible that the aforementioned limits of the CI theorisation are related to an insufficient exploration of how its processes are nested in three different levels of manifestation: micro, emergence and macro (Salminen 2012). The macro-level refers to the effects of CI on the group performance. It is generally studied as a statistical phenomenon. The micro-level is seen as a complementary perspective to the macro-level and refers to the individual characteristics of the group's members that participate to collective intelligence. Unfortunately, despite their expected complementarity, few elements allow us to articulate micro and macro phenomena. Finally, the emergence-level can be defined as the properties of CI that emerge from interactions and refer to the interface between the micro and macro levels. This dimension "remains under-explored in research despite its importance for an in-depth understanding of CI processes" (Salminen 2012). Research thus need to "further explore the emergence level of CI to better understand its underlying processes" (Salminen 2012). Studying the emergence-level of CI is particularly relevant as it also allows to consider collective intelligence as "a complex system capable of self-eco-organization" (Singh et al. 2013) and a system that "organizes itself according to its environment, because it draws energy and information from it" (Morin, 2014). As mentioned by Zaïbet (2007), "Collective intelligence underpins the existence and harnessing of cognitive, relational and systemic processes", leading to an interactionist approach of collective intelligence, in which collective intelligence is perceived as "the interaction between the organization and the environment through the interpretation that creates and defines a language and a mode of coordination between people". (Ribette, 1996; Zaïbet, 2007). Following this definition, the interactionist approach of collective intelligence places the study of interpretative phenomena and their social regulation at the epicentre of collective intelligence.

The systemic and interactionist approach of collective intelligence echo with the fundamental notions of social psychology: the paradigm of symbolic interaction (Mead 1934), microsociology (Blumer 1962), and the order's interaction (Goffman, 1985), that are known to explore the link between sense-making and cognitive/social regulation processes. Coupled with the communication sciences, these theories are commonly used since the 50's in interaction studies. This with the aim to explore how groups and individuals regulate themselves to improve collaborative reasoning in the paradigms of small groups, problem-solving and decision-making. Nowadays, these conceptualisations are generally absent from CI publications despite their obvious similarities and overlaps.

Regarding the subcomponents of CI, it is worthy to question how collective intelligence articulates in small groups during problem-solving. Small groups definition relies on a specific size (between 3 and 20) as well as several characteristics (De Visscher, 2010. First, these groups usually interacting for problem-solving in face-to-face situations rather than through online communities. Second, these groups are in immediacy, actively engage in the task to perform. Third, small groups underline a group identity such as a family, a friend group, a sport club or co-workers. Fourth, the small group members need to have a purpose to stay together. Fifth, the members are to be co-dependant and consequently influence themselves mutually. Finally, they share an important affective life). In application, small group appear to "outperform any independent individual"(Trognon et al. 2011). These groups are also cooperative (positively inter-dependent) while generally outperforming most of competitive groups in almost every fields (Trognon et al. 2011). The aim of these small groups is generally directed toward task performance such as "resolution tasks" (independent) and "consensus tasks" (collective). The small groups mode of interactions is based on free-discussion, especially in problem solving situations, which are seen as "an interface between the social and the individual, because it constitutes a mechanism for sharing cognitions, as well as a mechanism for producing collective intentionality" (Trognon et al. 2011). As a reminder, the notion of free discussion refers to the order's interaction theory defined as "the efficiency, in interaction, of a common sense as the first condition of possibility for interaction" (Goffman, 1981). Order's interaction correspond to the interface where systems of beliefs, representations, evaluations and social norms are produced and reproduced, characterizing the cultural and ideological processes of a society or of a particular social group (Trognon et al. 2011). Order's interaction is governed by its own rules, with its own consistency (Bonicco 2007), which means that it is "irreducible to the psychologies of individuals as well as to the sociologies of social macrostructures" (Francou 2015).

Small groups' dynamics in problem-solving and decision-making are particularly studied in social psychology, communication sciences and management. One definition of verbal interaction focusing on them as a negotiation about the meaning of events (a word, a situation, a behaviour…) (Roulet et al., 1991). This negotiation promotes the emergence of a shared cognition employed to perform carry-out a decision-making process (Trognon, 1999). Usually, decision-making processes respond to logical and ecological rationalities that organize interpretative phenomena, regulation processes, and behaviours (Sperber and Wilson 1995; Guercini et al., 2014 ; Trognon, 2013). Logic rationality refers to the rational approach strategies used by actors in interaction (Sperber and Wilson 1995; Guercini et al. 2022), while the ecologic rationality refers to the adaptative functioning subsequent to the specific interaction context, including the order's interaction and more broadly "common, emotions, norms, rules" (Goffman, 1985; Guercini et al. 2022).

In sum, despite their similarities, it is possible that the identified lack of sufficient theory devoted to collective intelligence emerged from the artificial distance existing between the small groups/decision-making theories and collective intelligence theories. One argument in favour of this position can be observed through the under-exploration of the emergence-level of CI (that precisely correspond to the CI's study of small groups) (Salminen 2012). A better comprehension of collective intelligence thus implies a study of interactions (and regulation processes) that emerged in these groups. To do so, the scope of studies should focus on the group's dynamics and relationships at the human scale, as supported in the paradigm of small groups, to bring a complement to studies on crowdsourcing and individual characteristics.

In this specific context, we conducted a qualitative systematic review of interactional factors that enhance or limit collective intelligence in small groups. The main objective of this article is to isolate the predictive factors inherent to the group's dynamics known to contribute to collective intelligence in small groups. These results, currently scattered in the literature, will provide a suitable framework for future explorations of the collective intelligence in small groups setting. This systematic review aim to connect separated theorisations for a more efficient theorisation of CI connected with microsociology, and problem-solving in small groups.

## 2 Method

Following the PRISMA guideline (Liberati et al., 2009; Moher et al., 2015), we carried out a systematic review registered on Prospero under the ID number XXXXXXXXXXXXXX. The main objective of this study is to identify the interactional factors that facilitate or limit the emergence of collective intelligence processes in small groups.

### 2.1 Search strategy

Between February 2021 and January 2022, we screened 7 databases selected for their relevance to the topic: "*Web of Science*", "Springerlink", "*CAIRN*", "*Sciencedirect*", "*APA PsycArticles and PsycINFO*", "*SAGE*", and "*Taylor & Francis*". An additional search conducted in "*Google Scholar*" ensured that potentially missed articles were collected. The keyword "*collective intelligence*" was crossed in databases with the following keywords: "*small groups*", "*interaction/interactionism*", "*symbol/sym-*

*bolic*", "*politeness*", "*relationships*", "*meaning*", "*interpretation/interpretative*", "*sense-making*". We used the following advanced search algorithm in databases using Boolean connectors:

1. TI= (collective AND intelligence) OR AB= (collective AND intelligence).

2. AND TS= (small groups OR interaction* OR symbolic* OR politeness OR relationships OR meaning OR interpretative* OR sense-making).

3. NOT TI= (web OR crowdsourcing OR swarm OR crowds OR artificial).

*Note* TI=Title contains exactly; AB=Abstract contain exactly; TS=Topic subject contain; *=or related terms.

### 2.2 Scope and inclusion criteria

The scope of the research focuses on the interactional factors that favour or limit collective intelligence in small groups in face-to-face interactions setting and small online communities. We therefore excluded articles about swarm/artificial intelligence systems and crowdsourcing activities. The inclusion criteria are interactional factors inherent to the collective intelligence of humans that appears in small groups. Exclusion criteria were: computational and artificial systems, crowdsourcing and swarm intelligence. We also excluded books, book chapters, conference papers, editorials, webpages, theses, non-English articles, and articles out of our publication range (2000–2021). The research algorithm was readapted when necessary to fit with the specific constraints of certain search engines (supp. data 1).

### 2.3 Screening and bias assessment

Two researchers (X.X. and X.X.) conducted a dual evaluation of the articles. Identification and screening of articles has been performed independently while the eligibility and selection phases were conducted jointly. Potential disagreements were arbitrated by a third examiner (X.X.). The articles were screened through their abstracts. Out-of-scope articles were excluded. The remaining articles has been fully covered for eligibility. When the full text was not available, authors were contacted (annexe 3).

We perform a risk of bias assessment with the AXIS Tool for quantitative studies (Downes et al., 2016), COREQ for qualitative studies (Tong et al., 2007) and JBI Critical Appraisal Checklist for Systematic Reviews and Research Syntheses. From the 371 out of 2757 articles first identified in the databases, 27 articles were finally included in the systematic review (details in Fig. 1). After carrying out a bias assessment (supp. Data 2), we proceeded to the data extraction (Table 2; supp. Data 3) of the selected articles before presenting the results.

### 2.4 Data extraction and organization

The data extracted from the articles focus on factors related to the barriers and facilitators of collective intelligence in groups and their impacts on group performance (nature of tasks, decision-making patterns, personal and interpersonal characteristics, aggregation effects, bias correction, influence games and leadership, etc.). Additionally, we extracted data related to the effects and impacts of collective intelligence on individual and group productions (individual/group improvement, decision-making accuracy, problem-solving duration and strategies, conflict management, etc.). We considered both qualitative observations (discursive analyses, interviews, etc.) and quantitative measures of effects. The statistical measures presented in the results are the $r$ value (correlation coefficient between two variables); the $p$ value (significance of a correlation); the $\beta$ value (standardized regression coefficient); the $R^2$ value (coefficient of determination); and the $z$ value (number of standard deviations between a value and the mean). The data presented in Table 1 summarise the main information provided in the articles (authors, date, field, country, aims/objective, article type, method, population, results). The data are presented in the results section based on a thematic analysis that revealed the main themes of the articles. We used the distinction between the micro, emergence, and macro levels of CI (Salminen 2012) to organize these themes.

## 3 Results

### 3.1 Overview

Our final selection comprehends 27 articles:1 meta-analysis, 21 quantitative studies, 4 qualitative study and 1 case study. The articles present good methodological qualities (21 articles assessed as "good", 5 as "fair", and 1 as "average"). Regarding the origin of the publications, most of them come from westernised countries (USA = 10; UK = 3; Switzerland = 2; Netherlands = 1; Norway = 1; Germany = 2; Italy = 1; France = 1, Finland = 1, Lithuania = 1) and 3 from east Asia (Taiwan = 1; Singapore = 1; China = 2). The study fields of selected articles are psychology ($n$ = 17), management ($n$ = 7), education ($n$ = 2) and sociology ($n$ = 1). The study populations are students ($n$ = 12), general population ($n$ = 9), simulations ($n$ = 3), workers of a specific company ($n$ = 2), researchers ($n$ = 1).

### 3.2 Micro-level of collective intelligence

#### 3.2.1 Collective intelligence in one mind

Most of the studies demonstrated that an average of two guesses from one individual is more accurate than either guess alone (Vul and Pashler 2008). When individuals are requested to provide a second guess during an estimation task, they usually bring additional information demonstrating that the first guess does not provide all the available information (Vul and Pashler 2008). In addition, the benefit of averaging is greater in a delayed condition than in an immediate condition ($p < 0.05$), suggesting that individuals are biased by their first response and demonstrate an anchoring effect (Vul and Pashler 2008). Additional results confirm that "individuals can simulate a diverse society in one mind but this effect does not outperform asking to one another person" (Rauhut and Lorenz 2011). Finally, other mechanisms than the wisdom of crowds might be involved in CI, such as. self-discussion, regulation of emotions and wilder speculations (Rauhut and Lorenz 2011).

### 3.2.2 Effects of individual intelligence on CI

Collective intelligence (*c* factor) predicts group performance (Study (1) ß = 0.51, $p=0.001$; Study (2) ß = 0.36, $p=0.0001$). However, average and maximal individual intelligence are not predicator of group performance (Woolley et al. 2010). Individual intelligence is a significant predictor of task performance when the task was performed alone ($r=0.33$, $p=0.009$), yet, this factor becomes not significant when applied to the group task (Woolley et al. 2010). Average individual intelligence and the intelligence of the highest-scoring team member are moderately correlated with *c* ($r=0.15$, $p=0.04$; $r=0.19$, $p=0.008$; respectively). Moreover, *c* is positively and significantly correlated with the proportion of females in the group ($r=0.23$, $p=0.007$), and more precisely with the social sensitivity of group members (ß = 0.33, $p=0.05$) (Woolley et al. 2010). Complementary results show that the percentage of women in the group acts positively on collective emotional intelligence (ß = 0.25, $p=0.004$), with strong effects on cohesion (ß = 0.36, $p=0.001$) and relationship conflicts (ß = -0.26, $p=0.02$) (Curseu et al. 2015). Moreover, cohesion (ß = 0.41, $p=0.001$), relationship conflicts (ß = -0.26, $p=0.002$) and affective similarity (ß = 0.23, $p=0.007$) have significant associations with group effectiveness (Curseu et al. 2015). These results demonstrated that groups with better emotional competencies are more cohesive and experience less conflicts than others, increasing the quality of relationships and therefore group effectiveness (Curseu et al. 2015).

Unfortunately, a recent replication of Woolley et al. (2010) studies only identified individual intelligence quotient (IQ) as significant variable for group performance (ß = 0.76, $p<0.001$) (Bates and Gupta, 2016) while female proportion (ß = 0.12, $p=0.447$), reading the mind in the eyes (RME) test results (ß = -0.11, $p=0.520$) were not significant (Bates and Gupta, 2016). Further research demonstrates that *g* (general intelligence) and *ToM* increase the ability of groups to engage in collective action to sustain resources. (ref). However, *g* only improves the ability of groups in maximising the harvest of knowledges (Freeman et al., 2020). Groups with high levels of *g* and *ToM* also present a better ability to solve a complex collective action problem, they engage in more effective collective action and are more consistent despite social or ecological change (Freeman et al., 2020). In contrast, the degree of g and ToM needed by groups depends on the nature and complexity of the tasks (social or ecological), which become particularly relevant in highly complex problem-solving (Freeman et al., 2020).

### 3.2.3 Cognitive style diversity and individual rationality

The relationship between cognitive style diversity and collective intelligence followed an inverted U-shape (quadratic relationship, β = -0.91, $p=0.03$) (Aggarwal et al. 2019). Diversity in groups acts as an essential component for CI. An average cognitive diversity positively and significantly impacts CI and team learning while a extreme low and extreme high diversity negatively impacts CI (Aggarwal et al. 2019). Working in diverse groups marginally predicts better individual performance (β = −0.37, $p=0.06$). Aggregate forecasts from diverse groups appear better than aggregate forecasts from homogeneous groups (β = −0.56, $p=0.01$) (Pescetelli et al.

2020). Finally, beneficial effect of diversity on individual performance is positively affected by group size, suggesting that individual interactions with diverse peers is more beneficial in large than small groups ($\beta = 0.82$, $p = 0.004$) (Pescetelli et al. 2020). Similar to the results observed for cognitive style diversity, the relationship between average collective knowledge level and degree of individual irrationality also follows an Inverted U-shape relationship in simulation. A little presence of irrationality, rather than complete rationality or excessive irrationality, can produce superior knowledge (Xu et al., 2016). When individual irrationality = 0, the collective may be trapped in an initial solution quickly(Xu et al., 2016).

## 3.3 Emergence-level of collective intelligence

### 3.3.1 Intermittent social influence

Social influence brought range-reduction and confidence effects that diminish diversity in groups without improving their accuracy and performance (Lorenz et al. 2011). Range-reduction effect implies that the group becomes less reliable in estimating the truth when exposed to social influence (Lorenz et al. 2011). The confidence effect reflects that opinion convergence improves individuals' confidence in their estimations without an accuracy improvement of the group's estimation performance (Lorenz et al. 2011). In these cases, groups engage in a convergence process that does not improve the collective (Lorenz et al. 2011). Further research demonstrate that intermittent social influence provides "benefits of constant social influence without the costs" (less diversity of solutions), with individuals learning from each other while maintaining a high level of exploration (Bernstein et al. 2018). Groups with the intermittent social influence condition (IT) found the optimal solution as frequently (in 48.3% of trials) as groups with no social influence (NT) (44.1% of trials), and better results compared to groups with constant influence (CT) (33.3% of trials) (Bernstein et al. 2018).

### 3.3.2 Team size, participation and social loafing

Average performance increases with person-hours (activity time of each member of the group) ($\beta = 0.726$, $p < 10-7$) (Mao et al. 2016). Smaller teams aren't more effective than large team: even if individual productivity decreased with team size. A positive effects of coordination (improvement in recall and precision) is also recognised in dominating the negative effects of social loafing (Mao et al. 2016). By extension, there is currently no scientific consensus about the optimal team size for collective intelligence: participants are sometimes in favour of increasing group size, others mentioned it as not relevant to the quality, and others are contrarily in favour of smaller groups (Mao et al. 2016; Mačiulienė et Skaržauskienė, 2016). In simulation, results suggest that network density has a positive relationship with collective performance (Xu et al., 2016). Dense networks lower the diversity, where sparse networks may be able to reach consensus quickly, at the expense of unsatisfying quality and unity of knowledge (Xu et al., 2016).

### 3.3.3 Trust and consensus tasks

The level of consensus grows when the strength or the density of social relationships increases (Massari et al. 2019). Moreover, group performance rises when the level of consensus grows, but when the level of consensus is too high it diminishes the group performance (Massari et al. 2019). Plus, the relationship between scope of trust/distrust and group performance depends on the strength and density of social relationships (Massari et al. 2019). More precisely, a low scope of distrust can be useful for the performance (as it prevents polarization in consensus andmaintains exploration), yet this applies only in groups with moderately high-strength and high-density social relationships. Any scope of distrust is detrimental to the performance of groups with low-strength and low-density social relationships (Massari et al. 2019). Other results demonstrated that errors were larger (worse performance) for initial ($\beta = 0.62$, $p < 5.81e-12$), revised ($\beta = 0.69$, $p < 7.73e\text{-}15$) and final ($\beta = 0.23$, $p = 0.01$) forecasts compared to consensus forecasts (Pescetelli et al. 2020). These results indicate an accuracy improvement due to social interaction (Pescetelli et al. 2020).

### 3.3.4 Dynamic leadership

Research observed that individuals choose to respond earlier (with the potential to influence other group members) or to wait for social information depending on their personal results (correct or wrong) on previous questions. This is the reflection of a dynamic leadership in decisions (Kurvers et al. 2015). During pooling 2 (replication of the task), individuals (83.9%) made better decisions ($z = 2.9$, $p = 0.003$), had a higher probability of changing their decision ($z = 25.70$, $p < 0.001$), and a higher probability of being correct in that collective decision ($z = 5.06$, $p < 0.001$). This highlights the "positive effects of flexibility in decisions" (Kurvers et al. 2015). In parallel, collective improvement rise ($z = 2.25$, $p = 0.025$) with the time that the individuals who were wrong during pooling 1 took to respond during pooling 2. This shows that the CI effect is a result of the self-organization of the groups and not a result of the availability of social information (Kurvers et al. 2015).

In sum, groups can self-organize according to the accuracy of information of their members, demonstrating flexible and dynamic leadership leading to an improvement in collective decision accuracy (Kurvers et al. 2015). In other study, participants defined self-organization and leadership through three groups of decisions: structure decisions, leadership solutions and conflict management (Mačiulienė et Skaržauskienė, 2016). In virtual settings, data show that the participants take a more prominent role in the communication and interaction: 76.7% of participants mentioned in post-survey questions that a sense of community had arisen, with an average of 64.40% agreeing about the usefulness of this (Garreta-Domingo et al., 2018). Authors suggest that the social dynamics of such networks are driven by a special kind of community named pop-up communities characterised by their purposefulness (they emerge for a specific purpose only) and their temporariness (they disappear once they have outlived that purpose) (Garreta-Domingo et al., 2018). These results joint the observations of Hansen et al. (2010) when they described the formation of spontaneous ad hoc sub-teams to manage team projects.

#### 3.3.5 Effects of working environment and communications tools on CI

Observations of workers in workplace suggested that the problem-solving ability of decision makers is characterised by very short face-to-face interactions, using simple rules that are effective for consistent improvisation in an unpredictable environment. These interactions imply articulation of divergent and convergent modes of thought, an awareness of the situation and the formation of adaptive ad hoc sub-teams (Hansen et al. 2020). A lack of demonstrative data representing the authors' interpretations in their articles should be considered as a limit of this study. Other results show that teams demonstrated higher collective intelligence ratios as the project progressed while the individual intelligence ratios varied over different communication methods and tasks (Kim et al., 2011). The provided interpretation made by the authors was that the preferable methods probably meet the demand of reducing cognitive burden on individual members (Kim et al., 2011). For small online communities: virtual accessibility, non-virtual relations and team management where consider as a prerequisite for group dynamics (Mačiulienė et Skaržauskienė, 2016). The distant time and space specific to online communities provides possibilities to ensure participants' mobility and reduction of costs (Mačiulienė et Skaržauskienė, 2016). Anonymity allows independence from external influences fosters creativity but reduce the possibilities to ensure the respect of generally accepted norms (Mačiulienė et Skaržauskienė, 2016). Other results considered engagement and focused attention in three co-creation environments (paper-based, 2D Jamboard platform, CoSpaces virtual reality) (Hsin-Yun, Chih-Yuan Sun, 2021). They demonstrated that the effect of the co-creation environment is not significant for behavioural engagement ($F=1.01$, $p=0.32$), cognitive engagement ($F=0.29$, $p=0.75$) and focused attention ($F=0.64$, $p=0.53$) (Hsin-Yun, Chih-Yuan Sun, 2021). However, the effect of the co-creation environment highly impacts ($F=6.25$, $p=0.003$) emotional engagement (Hsin-Yun, Chih-Yuan Sun, 2021).

### 3.4 Macro-level of collective intelligence

#### 3.4.1 General collective intelligence factor in groups

As Spearman deduce a factor *g* (general intelligence), authors found a factor *c* for collective intelligence. This factor explains group's performance on a wide variety of tasks (43% of the variance, 44% in study 2) (Woolley et al. 2010). The next factor accounts for only 18% (20% in study 2) of the variance, providing support for the existence of a single dominant factor *c* underlying group performance (Woolley et al. 2010). These results show that general collective intelligence factor predicts task performance (Study (1) ß = 0.51, $p=0.001$; Study (2) ß = 0.36, $p=0.0001$) (Woolley et al. 2010). The authors' interpretation suppose a more complex phenomenon than the aggregation of information in CI (Woolley et al. 2010). A study replication in the context of computer-mediated communication (CMC) showed that the first factor accounted for 42% of the variance, but the second factor accounted for 36%, suggesting two dominant factors rather than an emerging intelligence factor in this specific context (Barlow and Dennis 2016). An in-depth analysis of factors that could explain this difference did not isolated significant differences between the two studies (Barlow and Dennis 2016). Authors conclude that the factor found by Woolley et al. (2010) is not a general factor of collective intelligence inherent to groups under all conditions but rather a measure of a group's ability to work well in specific settings (face-to-face, online using "test battery" software, or with specific tasks) (Barlow and Dennis 2016). Other results demonstrated that the factor *c* emerges clearly across communication media (face-to-face vs. online), group contexts (short-term ad hoc vs. long-term) and cultural settings (US, Germany, Japan) and explain about 40% or more of the variance in all cases (Engel et al. 2015). CI scores were a strong positive predictor of performance on the task (ß = 0.24, $p=0.058$) (controlling for communication media); demonstrated a significant positive correlation between the average scores received by student raters and the team's CI scores ($r=0.25$; $p=0.008$). These latter were a much stronger predictor of student team performance than single task (Engel et al. 2015). These results suggest underlying similarities in the basic interaction patterns supporting human group performance, despite differences in communication modes, group contexts, and cultural settings (Engel et al. 2015). In the specific context of professional teams playing online game, study showed that one factor accounting for 38.38% of the variance whereas the next factor explained 14.77%, giving additional support to the conclusion of a single dominant collective intelligence factor in groups (Kim et al. 2017). Consequently, CI significantly predicted highest skill tier at time of study (ß = 0.29, $p=0.01$) and 6 months later. In addition, there is no difference on communication through in-game text chat, online voice chat or face-to-face for CI, confirming previous results of Engel et al. (2015). Other results also supported that collective intelligence is positively and significantly related to team learning ($\beta=0.29$, $p=0.007$) (Aggarwal et al. 2019). Then, collective intelligence and collective decision-making have a positive relationship in simulations ($R^2=0.528$) and field studies (McHugh et al. 2016). Finally, collective emotional intelligence have a strong relationship with group effectiveness through cohesion (ß = 0.41, $p=0.001$), relationship conflict (ß = -0.26, $p=0.002$) and affective similarity (ß = 0.23, $p=0.007$) (Curseu et al. 2015).

### 3.4.2 Collective intelligence in scientific research

Authors found that research's motivations for mobilizing CI are due to the limits of traditional research methods, the complexity of research questions and the personal pleasure to working in teams (Nguyen et al. 2019a). The barriers identified by researchers in mobilizing CI are the lack of evidence-based guidelines for optimal method, the complexity of recruiting and engaging the community of participants, and the difficulties in disseminating the solution generated by CI (ibid.). Good practice advice for conducing CI projects proposed by researchers are to establish a coordination team, create a set of common rules, identify the research questions and the communities of participants, determine methods to evaluate solutions created by CI and decision-making, organize the communication activities, engage participants through responsive communication and disseminate solutions created by CI for beneficiaries and CI participants (ibid.). A case study in online learning environment highlighted the group 'development of a shared understanding of a set of joint research questions through elaboration, clarification and negotiation processes (Mäkatilo-Siegl, K, 2008). The shared theoretical framework emerged through both shared understanding and individual perspectives (Mäkatilo-Siegl, K, 2008). Additionally, a meta-analysis of 145 reports showed that CI was mobilized to generate ideas, conduct evaluations, solve problems, and create intellectual outputs (Nguyen et al. 2019a). Most studies (76%) were open to the general population, without any restrictions on the participants' expertise (Nguyen et al. 2019a). More precisely, participants contribute to projects through independent contribution (50.34%), collaboration (41.28%), competition (33.23%) and playing games (16.11%) (Nguyen et al. 2019a). Finally, 61% of the articles reported methods to evaluate participants' contributions and decision-making processes (Nguyen et al. 2019a).

## 4 Discussion

The diversity of presented factors and methods does not allow for a statistical comparison of their impacts. Among these factors, studies do not identify elements to be prioritized for collective intelligence. These factors remain essential at several levels, and their articulation is key to an optimal manifestation of collective intelligence. Collective intelligence is (above all) a group characteristic (Vul and Pashler 2008; Rauhut and Lorenz 2011) that is positively and significantly correlated to group performance (Woolley et al. 2010; Aggarwal et al. 2019). Results demonstrated that collective intelligence depends on individual factors (individual cognitive and social/emotional intelligence and therefore meta-cognition abilities, cognitive style, self-regulation processes); interactional factors (influence games, leadership, diversity, distribution of speaking turns, trust and distrust) ; functional factors (task form, decision-making tools, working environment, ad hoc groups).

Studying collective intelligence through small groups highlights dimensions that are not directly observable in crowdsourcing: collective intelligence effects in one mind (Vul and Pashler 2008; Rauhut and Lorenz 2011), links between individual cognitive/emotional intelligence and collective intelligence (Woolley et al. 2010; Curseu et al. 2015; Bates and Gupta, 2016), conflict management, cohesion and inspiration in relations (Curseu et al. 2015; McHugh et al. 2016), effects of trust and distrust in consensus tasks (Massari et al. 2019), and problem-solving abilities in the working environment (Hansen et al. 2020). Moreover, the study of small groups brings complementary results to crowdsourcing about the need for a participative and democratic tool to enhance CI (Malone and Klein, 2007; Piccolo et al., 2018, Vercammen & Burgman, 2019) : results demonstrated that this tool needs to rely on a balance consensus (Massari et al. 2019) that allows a participative and dynamic leadership (Kurvers et al. 2015), promotes intermittent social influence (Bernstein et al. 2018) and defines the nature of the task to properly determine the *g* and *ToM* needed (Freeman et al., 2020).

Additionally, results converge on the importance of balanced factors for collective intelligence (inverted U-shaped): moderate diversity (Aggarwal et al. 2019), flexible leadership (Krause, 2015), intermittent social influence (Bernstein et al. 2018), slight irrationality (Xu et al., 2016), moderate *g* and *ToM* (Freeman et al., 2020), balanced level of consensus and balanced trust/distrust (Massari et al. 2019) positively and significantly impact collective intelligence. According to these results, a too high or too low level of these dimensions negatively impacts collective intelligence. These results support the idea of group functioning geared towards regulation by complementarity rather than the homogenization / centralization of cognitions and behaviours. Moreover, all of these factors promotes exploration during group-decision, while the moderate/balanced dimension of these factors promotes frameworks to collaborative reasoning and decision-making. These factors, by maintaining both exploration and reliance in groups, appears as essential dimensions to address well-known challenges of collective intelligence, as getting beyond group-thinking (Sunstein and Hastie 2015) and ideological polarization (Kahan 2013). However, the notion of "trust/distrust" need to be better conceptualized in researches about collective intelligence: theoretical framework now provide distinction between interpersonal trust and interorganizational reliance (Mouzas et al. 2007). These dimensions can be "high" or "low", as it is for the scope of trust/distrust but tend to formalize different relationships regarding their organization (fragile, expedient, stable, personal) (Mouzas et al. 2007).

Presenting results through micro, emergence, and macro levels of CI serves to illustrate a systemic perspective of CI through issues that are specific to each level, with the objective to demonstrate the complementarity of these dimensions. Micro-level refers to individual characteristics as *g* and *ToM*, socio-emotional abilities and inner diversity. These characteristics contribute to collective intelligence when groups promote them in relations. This functioning will contribute to the organization of group processes, as the first type of interaction that can be observed between the micro and emergence levels. Moreover, mutual adjustment and self-regulation processes (Goffman, 1985) influence the characteristics that individuals will manifest among themselves. This adaptive functioning accounts for the second type of interaction between emergence and micro levels. The macro-level can finally provide a set of feedback about project's progression and decision-making (in term of performance), allowing groups' members to adjust to themselves in relation. Currently, even if this systematic review identified several factors of collective intelligence, an in-depth study of interaction is needed if we want to better understand how these factors self-regulates in groups to promote CI. Regarding results, we think the paradigms of problem-solving and decision-making in small groups can enrich research about CI processes through an in-depth study of interaction.

## 5 Recommendations

The factors identified in this review highlights properties that promote collective intelligence in small groups. Future research and practices should benefits from the moderation of these factors in groups. However, a better comprehension of interaction and regulation processes are needed to demonstrate how groups and individuals organizes themselves through these factors to produce collective intelligence.

Authors pointed a "lack of sufficient explanatory theory" (Bonabeau 2009; Luo et al. 2009; Schut 2010; Salminen 2012) due to "under-exploration of emergence-level" in collective intelligence studies (Salminen 2012). Emergence level refers to the study of interaction processes that occurs in groups, and the study of interaction between micro and macro processes of CI. However, CI studies appears polarized through crowdsourcing, that "underpins all studies on collective intelligence" (Nguyen et al. 2019a). Crowdsourcing refers to the study of CI as a statistical phenomenon in large online communities (macro-perspective). More diversity are needed in studies to explore dimensions related to collective intelligence that are not embedded by crowdsourcing, as interaction processes in daily routines and small groups.

For this, collective intelligence should benefit from social psychology and micro-sociology contributions : paradigm of symbolic interaction conceptualized interaction as a sense-making process (Mead 1934; Blumer 1962) that emerge from negotiation (Roulet, 1991) and through the construction of shared references (Zaïbet, 2007; Heylighen 2013) ; microsociology studied interaction order (Goffman, 1985) as a systemic process that organize conducts (through social rules and rituals) ; problem-solving and decision-making in small groups apprehend dimensions related to CI (influence games, performance, complementarity, socio-emotional skills, groups' dynamics…). Finally, interlocutory logic allow us to study "how the dynamic of interlocution products both social and cognitive events" (Trognon 1999 ; Sorsana 2003) by analyzing co-construction processes in interaction, such as consent in negotiation (Mouzas and Ford 2018), shared understandings of rules and inter-cognitive representations (Mouzas and Henneberg 2015). All of these paradigms can provides frameworks to better study interaction processes that promote collective intelligence in small groups.

These considerations should respond to limits of current definitions about collective intelligence identified in introduction: the role of emotion is well-known in decision-making process ; small groups provide a framework that allow us to apprehend dynamics and characteristics of groups/individuals ; the study of interaction through interlocutory logic bring the interaction out of the "black-box" by observing regulation processes. Moreover, these paradigms could respond to limits mentioned about insufficient explanatory theory (Bonabeau 2009; Luo et al. 2009; Schut 2010; Salminen 2012) ; under-exploration of interactive dimensions of collective intelligence (Salminen 2012) and polarization through crowdsourcing in studies (Nguyen et al. 2019a).

## 6 Strengths and limitations

This article synthetized main results obtains in scientific literature about factors that promote collective intelligence in small groups, with the aim to provide a updated framework for future researches and practices. Additionally, this work tries to address, through disciplines of social psychology and microsociology, responses to the current limits observed in collective intelligence literature.

The wild diversity of themes and methods presented in this article didn't allowed us to perform a coherent meta-analysis on the subject. Secondly, due to the focus of this systematic review, it does not incorporate additional elements that are specific to crowdsourcing.

## 7 Conclusion

Research identified several factors of collective intelligence in small groups. Collective intelligence depends on balance diversity (Aggarwal et al. 2019), flexible leadership (Krause, 2015), intermittent social influence (Bernstein et al. 2018), slight irrationality (Xu et al., 2016), moderate *g* and *ToM* (Freeman et al., 2020), balanced level of consensus and moderate trust/distrust (Massari et al. 2019). These factors both maintaining exploration and cohesion in groups, improving decision-making, and preventing group-thinking/ideological polarization in groups without motivated reasonings (such as conflict of interest). However, an in-depth study of interactions that occurs in these groups is needed to provide essential understandings of regulation processes that organize these factors in interaction. Currently, regarding their specific characteristics and dynamics (De Visscher, 2010, Maisonneuve 2013), small groups appears to be an essential tool to promote collective intelligence (Hansen, 2010, 2020) and to study it (Zaïbet, 2007 ; Salminen 2012) if we want to address the limits observed in researches (Bonabeau 2009; Luo et al. 2009; Schut 2010; Salminen 2012; Nguyen et al. 2019a).

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### Declarations

**Ethical approval** The manuscript adheres to ethical guidelines specified in the APA Code of Conduct as well as author's national ethics guidelines.

**Conflict of interest** We have no known conflict of interest to disclose.

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