# Exploring the Influence of Self-determination in the Collective Intelligence of Collaborative Organizations

Alexandre Ribas Hortal[a b 1]

[1] alex@kozzak.net

[a] Laboratorio DHARMa
Universidad Tecnológica Nacional
Facultad Regional Mendoza
Rodríguez 273, Mendoza (Argentina)
dharma.frm.utn.edu.ar

[b] MediAccions
Research Group in digital media and culture
Universitat Oberta de Catalunya
Av. Tibidabo, 47, Barcelona (Spain)
mediaccions.net

Facundo Bromberg [a c 2]

[2] fbromberg@frm.utn.edu.ar

[a] Laboratorio DHARMa
Universidad Tecnológica Nacional
Facultad Regional Mendoza
Rodríguez 273, Mendoza (Argentina)
dharma.frm.utn.edu.ar

[c] Consejo Nacional de Investigaciones
Científicas y Técnicas (CONICET), (Argentina)
conicet.gov.ar

## Abstract

In recent years, positive correlations between some factors of collaborative group task processes and the increasing of collective intelligence (CI) have been presented. This work introduces an hypothesis that argues the existence of a new factor of positive influence for the increasing of collective intelligence in collaborative group tasks operating in cooperative environments: *self-determination*. Therefore, we present an argumentation based on Cooperative Multiagent Systems that spotlights the significance of self-determination in these particular environments. Furthermore, we also introduce a preliminary design of an experimental setup and a methodological framework for validating the hypothesis empirically in human organizations. Our propose consists on measuring, on the one hand, the level of self-determination from the individuals that participate on the decision-making processes, and on the other hand, on measuring the level of collective intelligence achieved by performing collaborative group task. Finally, we propose to use statistical analysis to explore if there are positive correlations between *self-determination* and *collective intelligence* in cooperative environments, such as collaborative organizations.



**Alexandre Ribas Hortal** is member of DHARMA Lab (UTN-FRM) and research fellow of Mediaccions Research Group (UOC). He is a Computer Science doctoral student in la Universidad Nacional de San Juan (Argentina). Undergraduate in Communication Studies (UOC) and with a Master degree in Information and Knowledge Society (UOC- IN3). His research focus on technologically mediated human collaboration and the exporation of diverse applications of Human-Computer Interaction and Artificial Intelligence to the problem of Augmented Human Collective Intelligence.

**Facundo Bromberg** obtained his Physics undergraduate degree in 1998 from the Instituto Balseiro of the Universidad Nacional de Cuyo, San Carlos de Bariloche, Argentina; and his Ph.D. in 2007 at the Computer Science Department of the Iowa State University, Ames, Iowa, USA. For the last 10 years he has been a full-time professor at the Universidad Tecnológia Nacional, Mendoza, Argentina, founding and developing the DHARMa Research Lab by successfully advancing a wide range of research projects in the Artificial Intelligence and Machine Learning disciplines, both academic and for the industry. His current research interests range from Computer Vision applied mainly to Viticulture and Biomechanics, Machine Learning applications, Probabilistic Graphical Models, and recently has explored diverse applications of Artificial Intelligence to the problem of augmented human collective intelligence.



**Keywords –** Collective Intelligence, Self-determination, Collaborative Organizations, Cooperative Multiagent Systems, Self-determinant Governance

**Paper type** – Academic Research Paper

# 1 Introduction

This work argues that individual self-determination empowers organizations to collectively take more intelligent decisions, under the assumption that the problems they are solving are collaborative, and the individuals that shape the organization can be considered minimally rational, i.e., the actions they decide to execute guarantee an increase of their performance in the environment (Russell & Norvig, 2004). According to (Romme, 1999), self-determination in an organizational or decision-making process is the ability of an individual to block collective decisions that he or she considers may negatively affect their expected utility. In turn, collective intelligence is understood as the collective ability to decide joint actions that allow improving the value captured from the environment, i.e., increase their utility.

This argument is based on the theory of Cooperative Multiagent Systems (Wooldridge, 2009, Ferber & Weiss, 1999), and arises from some considerations on how, in cooperative environments, there is an alignment between the level of individual expected utility, and the level of expected utility of the organization; in such a way that the organization only maximizes its utility when all its agents also maximize their individual utility (through the same joint action), and vice versa. In this context, rational agents having the ability to block actions that are considered to be detrimental to their expected utility, ensure that no not-intelligent joint actions are executed.

We also present an experimental setup for complementing the theoretical validation with an empirical one, by reporting the correlation between individual self-determination and collective intelligence. We introduce a methodological framework for measuring, for each decision made collectively, the level of self-determination self-perceived by individuals, based on tools for developing measurement models provided by the Self-Determination Theory (Ryan & Deci, 2000); together with a method for measuring the level of Collective Intelligence (CI metric) in collaborative group tasks based on tools introduced by (Woolley et al., 2010, Engel et al., 2014, 2015).

The interest to delve into factors of positive influence for increasing collective intelligence in these contexts is fundamented in its potential impact on new organizational typologies such as Collaborative Networked Organizations (CNO) that emerge in the context of research in Human-Computer Interaction and Collaborative Crowdsourcing (Engel et al., 2015, Bingham et al., 2015), focused on studying the potential for *the many to outperform the few* based on new collaboration opportunities resulting from novel means for people to access information, services and other resources (Camarinha-Matos et al., 2009; Dutton, 2008).

Furthermore, the demonstration of an existing positive correlation between individual self-determination and collective intelligence presents a two-fold motivation for designing human-centric governance systems that respect individual self-determination, such as the existing Sociocracy (Endenburg & Bowden, 1988), Holacracy (Robertson, 2007) or Sociocracy 3.0 (Priest & Bockelbrink, 2017), as well socio-technological artifacts for facilitating its adoption. On one hand they are rendered indispensable for increasing the collective intelligence of the organization adopting the governance system, while resulting in an increase in satisfaction of the needs of the individual humans that compose the organization.

In recent years, positive correlations between some factors of collaborative group task processes and the increasing of collective intelligence have been presented, both in groups collaborating face-to-face and on groups collaborating through socio-technological systems. Woolley et al., (Woolley et al., 2010) highlighted three factors that show strong correlations with the increase of collective intelligence in groups, and consequently can be considered as factors of positive influence: (1) the average of social sensitivity, i.e., the (average) ability to correctly detect the feelings and viewpoints of people by observing their facial features, (2) the number and distribution of speaking turns, and (3) higher proportion of women in groups. However, as far as we could investigate, there is no systematic research by these authors, or others, that focuses on exploring the level of self-determination from individuals who participate in a decision-making process as a factor of positive influence for the increasing of collective intelligence. Hence, we understand that this positive correlation is an unexplored factor that is worth investigating.

This paper is organized as follows. Section (2) presents and develops the main argument, providing definitions of the necessary concepts and explaining the causality of the proposed correlation, i.e., that the increase of individual self-determination leads to the increase of collective intelligence in particular environments. Next, Section (3) introduces the proposed experimental setup for validating the hypothesis empirically. On the one hand, in (3.1) a particular adaptation of the Self Determination Theory (Ryan & Deci, 2000) questionnaires for scale-building is proposed, in order to measure the level of self-determination from each individual participating in a decision-making process. On the other hand, in (3.2) the framework used by (Woolley et al., 2010, Engel et al., 2014, 2015) is introduced, used for measuring the level of collective intelligence of a group through the resolution of collaborative tasks. Finally, the main conclusions are presented in Section (4) and the references used in Section (5).

## 2 Self-Determination as an heuristic for Optimal Joint Policy search

In agent theory (Russell & Norvig, 2004; Wooldridge, 2009), intelligence is defined as the ability of an agent to choose those actions that maximize its utility in a work environment. The difficulty for finding these intelligent actions depends on some characteristics of the agent's working environment, namely, whether it is: *static* or *dynamic* (i.e., the environment behaviour can change over time or not); *deterministic* or *stochastic* (at any given state, the same action always produces the same outcome, that is, for the same action, the environment always transitions to the same successor state); *episodic* or *sequential* (either the optimality of future actions depends or not on the present action); totally or partially observable (agents can determine or not what is the current state of the environment), and *single agent* or *multiagent* (there are other rational agents operating in the environment or not). The latter can be further characterized as *cooperative* versus *competitive* environment (explained below). Each of these characterization results in an increasingly complex formalization of what is considered a solution to the artificial intelligence problem.

The simplest, yet realistic characterization of the problem in which our argument is framed considers a cooperative multiagent problem. A *multiagent system* can be understood as a system made up of more than one rational agents that has to be coordinated for learning those joint actions that allow them to maximize their utility in a given environment. Differently from the single agent case; in multiagent problems agents present interdependencies, that is, agents not only have to reason about which of their own actions are best for maximizing their individual utility, but they also have to reason about the effects produced by the other agents actions. In other words, agents has to learn the joint actions that maximize their utility, and their individual intelligence is measured in terms of these joint actions.

In the simplest workspace, i.e, the static, deterministic, episodic, totally observable, and single agent, a solution is a single action that guarantees a maximum return from the environment. When the workspace turns to be sequential, solutions becomes sequences of actions. This is the case for the well-known search and planning problems (Russell & Norvig, 2004), that help the agent to find objective states (i.e., they model the utility as zero for every state and some arbitrary non-zero positive value for the objective state). If the workspace is now stochastic (as well as sequential), sequence of actions are not appropriate, as the stochasticity of the workspace results in the same sequence reaching a whole set of possible states, with the objective state being only one of them, without certainty that it will be reached. What is required here is to maximize the probability of reaching that objective state. For that, solutions are expressed in terms of policies: functions from states to actions, that indicate what action should the agent execute in each state. A solution in these cases is therefore the optimal policy, the policy that maximizes the probability of reaching the objective state. For more general problems with a general utility function over the state space, the solution is the policy that results in the maximum expected utility extracted from the environment, computed from the expected utility that could be obtained starting from the initial state, and the expectation computed over all possible state trajectories the agent could traverse when acting on its policy, with bifurcations arising from the stochasticity of the actions.

Finally, in a multiagent system, agents present interdependencies, that is, agents not only have to reason about which of their own actions are best for to maximizing their individual utility, but they also have to reason about the effects produced by the other agents actions. In other words they have to learn which are the joint actions that maximize their individual utility. When the multiagent system is embedded in a sequential and stochastic workspace (and regardless of the dynamicity and observability of the environment), the solution for some agent is a joint policy that produces a maximum expected utility for that agent, that is, a function that indicates for each state (or observation in the more general case of partial observability), what is the joint action that when the agent starts at some initial state, guarantees to produce the long-run maximum expected utility for the agent. Interdependencies between the agents' actions may result in the impossibility to optimize the policy for each individual agents. In the particular case of cooperative multiagent problems, agents are motivated to coordinate themself because there is a solution that benefits all of them (win-win), as opposed to the competitive problems where the solution implies that if one agent maximize its utility, another may be harmed (win-lose). So in cooperative problems, there is a policy that guarantees, not only to maximize the expected utility of the collective, but also the expected utility of each agent.

In this context, self-determination can be understood as a sensory and cognitive heuristic for finding optimal joint policies, based on the fact that in cooperative environments, any joint action that is harmful to at least one of the agents, is harmful to the organization. Therefore, providing individual agents with the self-determinant ability to block joint actions that from her own perspective could be harmful to her own individual utility, results in the blockage of joint actions that most probably are not those recommended by an optimal joint policy for the collective. In this regard, individual self-determination works as a heuristics for reducing the search space for the optimal joint policy.

## 3 Design of the experimental setup

In order to empirically validate the correlation between self-determination and collective intelligence, we present a preliminary design of an experimental setup and a methodological framework for data gathering and data analysis that combines both, qualitative and quantitative methods based on (Zhou, 2019). Definitive questionnaires for measuring self-determination are not included.

The main purpose is to measure the level of self-determination from each individual participating in the decision-making of a collaborative joint action, together with the level of collective intelligence (CI metric) reached after executing the actions produced by these decisions. According to this, a particular adaptation of the scales offered by the Self-Determination Theory is proposed for measuring self-determination (Ryan & Deci, 2000), and the framework presented by (Woolley et al., 2010, Engel et al., 2014, 2015) for measuring the collective intelligence of groups, the IC metric, is introduced.

By obtaining these measures, it would be possible to study and validate if there are positive correlations between the level of self-determination from each individual participating in the decision-making and the level of collective intelligence (CI) arised by performing the group task. The measurement methods are explained in detail in the following sections.

### *3.1 Measuring self-determination*

In order to measure the level of self-determination, Self-Determination Theory (Deci & Ryan, 2000) offers tools for designing different scales based on self-regulation, which assess domain-specific individual differences regarding the types of motivation or regulation. Since, according to Self-Determination Theory, motivation can vary in the degree of being autonomous versus being controlled, or in other words can vary depending on the level of self-determination (Deci & Ryan, 2015).

The basis for designing our particular measurement tool are the questionnaires for measuring self-determination in work environments such as the Work Extrinsic Intrinsic Motivation Scale (WEIMS) (Tremblay et al., 2009). These questionnaires have been adapted for measuring self-determination in particular work contexts, also for virtual context such as crowdsourcing micro-tasks platforms (Naderi, 2014). However, to the best of these authors' knowledge, there are no questionnaires designed for properly analyzing the level of self-determination in collaborative decision-making processes. Instead, this aspect has been only partially covered in more general questionnaires related to the level of satisfaction at work (Deci et al., 2017). Thus, a questionnaire to carry out this concrete measurement would be designed following the proposal of (Zhou, 2019): a mixed methods model of scale development and validation analysis. This method introduces 5 different steps.

**Step 1:** Qualitatively investigating the scale construct. In this stage the phenomenon that is going to be studied is defined as the construct of the scale: self-determination. To this end, we will propose an ethnographic approach to carry out fieldwork (participant observation, semi-structured interviews) over different organizations operating with self-determinant governance structures in order to look into which issues may affect the levels of self-determination of individuals' decision-making, such as the decision-making mechanism; the invisible power structures (Freeman, 1970), i.e, informal networks that exercise dominance in the form of social pressure, or the overload associated with the inclusion of all individuals in decision-making processes.

**Step 2:** Converting qualitative findings to scale items. Transforming qualitative data to measurable items is a mixing strategy that indicates how qualitative and quantitative data are integrated. In this work, the main goal objective is to spotlight undercovered variables that can affect the levels of individual self-determination discovered in the field work, and classify them in the dimensions or levels of self-determination proposed by Ryan & Deci (Ryan & Deci, 2000). This work differentiates between autonomous motivation and controlled motivation and suggests that behaviors can be classified based on the degree to which they are autonomous or controlled. Therefore, they introduce a self-determination continuum showing types of motivation with their regulatory styles, loci of causality, and corresponding processes. From more self-determinant to nonself-determinant they distinguish between: (1) intrinsic regulation, (2) integrated regulation, (3) identified regulation, (4) introjected regulation, (5) external regulation, (6) amotivation. In order to explore and test the variables discovered in the fieldwork, a Lickert scale questionnaire would be designed for relating sets of questions with the different dimensions of self-determination proposed by Ryan&Deci (Ryan&Deci, 2000).

**Step 3:** Conducting mixing validation to review items' content-based validity. Mixing validation indicates that both qualitative approaches (reflection, debriefing, panel review) and quantitative methods (sorting and calculation) are used to validate that the selected items or constructs from the field work tackle exhaustively the construction of the scale to be measured.

**Step 4:** Administering the scale on the target population. The quantitative survey is a primary method to administer the new instrument (May, 2001). Accordingly, the questionnaire would be sent to a representative sample of the scale we want to measure. Issues related to the size and sample distribution requirements will be considered, specially that advanced statistical analysis, such as factor analysis, require hundreds of responses for each item.

**Step 5:** Conducting quantitative validation to examine item's construct-based validity. The responses of the items will be analyzed statistically and validated using factor analysis methods (Stevens, 2012).

### *3.2 Measuring Collective Intelligence (CI)*

As it have been shown in (Woolley et al., 2010; Engel et al., 2014; 2015), groups can be characterized by a collective intelligence factor that measures their ability to collectively perform in a wide range of different tasks, which allows the prediction of the groups' performance on other tasks in the future. That is, like individuals, groups have characteristic levels of intelligence, which can be measured systematically through the Collective Intelligence metric (CI metric) based on the statistical approach that psychologists used to measure individual intelligence (Woolley et al., 2015).

In all these experiments, three factors were significantly correlated with the collective intelligence of a group: (1) the average of social sensibility from group members, (2) the number of speaking turns, i.e., the groups where the conversation was dominated by some people express less intelligence than those where conversation is more distributed, (3) higher proportion of women in groups, since women show a better average on social sensibility. However, to the best of these authors' knowledge, there are no systematic research by these authors, or others, that focuses on exploring the level of self-determination of individuals who participate in a decision-making process as a factor of positive influence for increasing of intelligence collective. Consequently, we propose to use the CI metric tests used by (Woolley et al., 2010; Engel et al., 2014; 2015) for measuring Collective Intelligence. These tests are based on a selection of tasks from all quadrants of the McGrath Task Circumplex, a well established taxonomy of group tasks based on the coordination processes they require. These tasks include solving visual puzzles, brainstorming, making collective moral judgments, and negotiating over limited resources. Furthermore, these IC metric tests have been evaluated both, in face-to-face experiments and also in online experiments, i.e., technology-mediated, through a testing platform. Thus, we propose to adapt the online testing platform presented in (Engel et al., 2014;2015) to facilitate participation.

Finally, for exploring if there is a positive correlation between the level of individual self-determination and the increasing of collective intelligence in a group, we propose to embed the questionnaires designed to measure the level of self-determination to the online testing platform used by (Woolley et al., 2010; Engel et al., 2014; 2015) for measuring the CI metric from a group that solves collective task collaboratively. Accordingly, for each completed task we will obtain, on the one hand, the CI metric score associated with the task; and on the other hand, the level of self-determination expressed by each of the participating individuals. With this pairing, we will be able to explore if there are positive correlations through different statistical analyzes, i.e., we would be able to check if the tasks with a higher CI metric score are also those in which the participants express a higher level of self-determination.

## 7 Conclusions

In this work, we introduce the hypothesis that individual self-determination is a factor of positive influence for increasing collective intelligence in cooperative multiagent problems in sequential stochastic environments. To validate it, a theoretical argument has been presented as well as an experimental design to perform an empirical validation.

In section (2) an argument framed in agent theory (Russell & Norvig, 2004) is presented. As it have been shown, theoretically there is an existing positive correlation between self-determination and the increase of collective intelligence in cooperative multiagent systems because in this particular contexts, any joint action that is harmful to the organization is harmful to at least one of the agents, and vice versa. Consequently, as it has been shown, self-determination, i.e., the individual capacity of an agent to block collaborative joint actions when she thinks that it may affect her individual expected utility, serves as a heuristic to collectively compute the search for the optimal joint policy of the organization.

This heuristic is based on reducing the search space of the optimal joint policy by discarding those joint actions that sure are not in the optimal joint policy, i.e., that have been objected by at least one of the individuals, and therefore, are not collaborative. Consequently, it is assumed that when discarding non-collaborative actions, the remaining joint actions, those that are part of a joint collaborative policy, have a greater chance of being in or close to the optimal joint policy.

In section (3) an experimental setup has been presented, describing the tools for measuring both, the level of self-determination from individuals; and the level of collective intelligence in collaborative task solving (CI metric). Accordingly, these tools have been described and evidences from its validity have been presented, concluding that they are able for measuring the level of self-determination of different individuals participating in a joint activity (Deci & Ryan, 2015), and for measuring the level of collective intelligence of a group (CI metric) (Woolley et al., 2010; Engel et al., 2014;

2015). Furthermore, we showed how these tools have been adapted to particular situations previously (Tremblay et al., 2009; Naderi, 2014) and we introduced a methodological framework (Zhou, 2019) to properly validate an adaptation to the particular problem posed in this work .

Finally, we have offered an explanation of how the gathered data will be computed in order to test the correlations, demonstrating that the proposed experimental setup would be able for validating the main hypothesis presented in this work: individual self-determination is a factor of positive influence for the increase of collective intelligence in cooperative certain cooperative contexts.

## References


Bigham, J. P., Bernstein, M. S., & Adar, E. (2015). Human-computer interaction and collective intelligence. Handbook of collective intelligence, 57.

Buck, J.A.,&Endenburg, G. (2015). Sociocracy: The creative forces of self-organization.Rotterdam: Sociocratic Center. The Netherlands, Tech. Rep. Retrieved May, 8, 2015.

Camarinha-Matos, L. M., & Afsarmanesh, H. (2008). On reference models for collaborative networked organizations. International Journal of Production Research, 46(9), 2453-2469.

Camarinha-Matos, L. M., Afsarmanesh, H., Galeano, N., & Molina, A. (2009). Collaborative networked organizations–Concepts and practice in manufacturing enterprises. Computers & Industrial Engineering, 57(1), 46-60.

Deci, E. L., & Ryan, R. M. (2015). SDT: Questionnaires: Intrinsic motivation inventory (IMI).

Deci, E. L., Olafsen, A. H., & Ryan, R. M. (2017). Self-determination theory in work organizations: The state of a science. Annual Review of Organizational Psychology and Organizational Behavior, 4, 19-43.

Dutton, W. H. (2008). Collaborative network organizations: new technical, managerial and social infrastructures to capture the value of distributed intelligence.

Ferber, J., & Weiss, G. (1999). Multiagent systems: an introduction to distributed artificial intelligence (Vol. 1). Reading: Addison-Wesley.

Endenburg, G., & Bowden, C. W. (1988). Sociocracy: The Organisation of Decision-making:" no-objection" as the Principle of Sociocracy. Stichting Sociocratisch Centrum.

Engel, D., Woolley, A. W., Aggarwal, I., Chabris, C. F., Takahashi, M., Nemoto, K., & Engel, D., Woolley, A. W., Jing, L. X., Chabris, C. F., & Malone, T. W. (2014). Reading the mind in the eyes or reading between the lines? Theory of mind predicts collective intelligence equally well online and face-to-face. PloS one, 9(12), e115212.

Malone, T. W. (2015, April). Collective intelligence in computer-mediated collaboration emerges in different contexts and cultures. In Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems (pp. 3769-3778). ACM.

Malone, T. W. (2018). How Human-Computer 'Superminds' Are Redefining the Future of Work. MIT Sloan Management Review, 59(4), 34-41.

Naderi, B., Wechsung, I., Polzehl, T., & Möller, S. (2014, November). Development and validation of extrinsic motivation scale for crowdsourcing micro-task platforms. In Proceedings of the 2014 International ACM workshop on Crowdsourcing for Multimedia (pp. 31-36). ACM.

Olson, G. M., Malone, T. W., & Smith, J. B. (2013). Coordination theory and collaboration technology. Psychology Press.

Poblet, M., & Plaza, E. (2017). Democracy Models and Civic Technologies: Tensions, Trilemmas, and Trade-offs. arXiv preprint arXiv:1705.09015.

Priest, J., & Bockelbrink, B. (2017). Sociocracy 3.0. Sociocracy30. org.

Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. American psychologist, 55(1), 68.

Romme, A. G. L. (1999). Domination, self-determination and circular organizing. Organization Studies, 20(5), 801-832.

Romme, A. G. L., & Endenburg, G. (2006). Construction principles and design rules in the case of circular design. Organization science, 17(2), 287-297.

Russell, S., Norvig, P. (2004). Inteligencia artificial, un enfoque moderno. Pearson Educación, Madrid

Stevens, J. P. (2012). Exploratory and confirmatory factor analysis. In Applied multivariate statistics for the social sciences(pp. 337-406). Routledge.

Tremblay, M. A., Blanchard, C. M., Taylor, S., Pelletier, L. G., & Villeneuve, M. (2009). Work Extrinsic and Intrinsic Motivation Scale: Its value for organizational psychology research. Canadian Journal of Behavioural Science/Revue canadienne des sciences du comportement, 41(4), 213.

Wooldridge, M. (2009). An introduction to multiagent systems. John Wiley & Sons.

Woolley, A. W., Chabris, C. F., Pentland, A., Hashmi, N., & Malone, T. W. (2010). Evidence for a collective intelligence factor in the performance of human groups. science, 330(6004), 686-688.

Zhou, Y. (2019). A Mixed Methods Model of Scale Development and Validation Analysis. Measurement: Interdisciplinary Research and Perspectives, 17(1), 38-47.