Annals of Operations Research
https://doi.org/10.1007/s10479-026-07073-5

ORIGINAL RESEARCH

Bi-objective optimization of Co-working Networks: a public policy approach

Marco Alderighi[1] · Cristina Baroglio[2] · Mario Chiesa[3] · Tiziana Ciano[4] · Christophe Feder[4] · Valeria Figini[3] · Elisa Marengo[2] · Stefano Tedeschi[4]

Received: 12 August 2025 / Accepted: 20 January 2026

Abstract
This study proposes a bi-objective optimization model for co-working networks that jointly maximizes collaborative value while minimizing operational costs. The framework leverages Shapley Value theory to dynamically adjust objective weights based on each agent's marginal contribution, enabling public policy intervention grounded in territorial development objectives. Validated through a case study in the Aosta Valley using official ISTAT data, results demonstrate that dynamic Shapley-based weighting improves collaborative value by 12.7% and reduces operational costs by 8.8% compared to static strategies, while accounting for territorial externalities and environmental impacts.

Keywords Co-working Networks · Bi-objective optimization · Shapley Value · Coalition formation · Public policy · Territorial development

1 Introduction

In recent years, the world of work has undergone significant transformations, with an increasing emphasis on flexibility and collaboration (Bouncken et al., 2020). This shift has led to the rise of *co-working spaces*, which offer an alternative to traditional offices, fostering a dynamic and community-oriented work environment (Weijs-Perrée et al., 2019).

Co-working (see Section 1.1 for a short background) is not just a physical space, but a working method that promotes sharing, cooperation, and the creation of professional networks (Rus & Orel, 2015; Wang et al., 2022). The expectation is that the co-working environment fosters coalition formation through a process of mutual recognition of complementary skills, shared objectives, and resource optimization. These coalitions emerge when *agents* (professionals, freelancers, startups, small enterprises) recognize that collaboration can generate higher value than individual action. The potential benefits include knowledge sharing, resource pooling, risk distribution, access to new markets, and enhanced innovation capacity.

On the other hand, resources in co-working networks are limited by several factors: (1) physical space availability and infrastructure capacity, (2) public budget constraints, (3) environmental sustainability requirements, and (4) territorial carrying capacity. These limitations are not arbitrary but reflect real constraints that public decision-makers must consider when developing territorial policies. Resources can be improved through strategic investments,

Extended author information available on the last page of the article

Published online: 11 February 2026

infrastructure development, and policy interventions that enhance the territorial attractiveness for knowledge workers.

Co-working spaces are typically managed by public or private entities with specific territorial development objectives. In our framework, we consider public administration (local or regional government) as the primary decision-maker, responsible for setting strategic parameters that balance economic development with territorial sustainability. These managers have explicit objectives: maximizing social and economic utility for the territory while ensuring efficient resource allocation and environmental protection. An interesting approach to addressing these challenges is to consider professionals and companies that use co-working spaces as agents within a complex system, each with its own role and distinct contributions to the network (Ciano et al., 2024). These agents, based on their specific features, can influence the dynamics of interactions and coalition formation, generating synergies and opportunities (Alderighi et al., 2024). It is also crucial to consider resource limitations, such as time, space, and funding, to ensure equitable and optimal distribution. Although the literature offers well-established applications of both multi-objective optimization and the Shapley value, several limitations emerge that are particularly relevant in the context of co-working networks. In particular, many studies rely on static MOO models that do not allow for the incorporation of changing policy priorities or evolving collaborative behaviors. Similarly, the use of the Shapley value is often constrained by computational burdens that prevent its application to dynamic, seasonal, or evolving coalition scenarios. These factors highlight a gap between theoretical models and operational needs, a gap that our work addresses through a dynamic integration of objectives and a computationally scalable approach.

This paper aims to demonstrate how public policy considerations, embedded through strategic parameter choices, can enhance the effectiveness of co-working network optimization while ensuring alignment with broader territorial development objectives. Given the strategic and operational challenges inherent in managing co-working networks, an integrated bi-objective optimization model is proposed as a practical framework for navigating these complexities. This contribution helps bridge a significant gap in the literature by offering a novel approach tailored to the unique needs of co-working spaces.

Technically, the proposed model combines two objectives. It maximizes the collaborative value generated by the network of interacting parties and minimizes operational costs. In this way, it aims to ensure the network's efficiency and sustainability. The main goal is to provide an innovative and scalable solution to optimize the environmental conditions under which collaborations take place. We use the Shapley Value to determine each agent's marginal contribution. We then dynamically adapt the weights associated with the objectives in the model, based on the context of interest.

This work also explores how constraints imposed by limited resources can be handled effectively to support a fair and optimal distribution of resources. The proposed theoretical and practical framework can be a valuable tool in supporting the management of co-working spaces networks in their decision-making.

To validate the model, we use real demographic and economic data from official sources, including ISTAT (Italian National Institute of Statistics) and the Regional Geographic Information System of the Aosta Valley. We combine these data with optimization algorithms to determine optimal coalition configurations in the geographic area of Valle d'Aosta. The approach can easily be generalized to other geographic contexts and applied to reason about the proposal's scalability.

1.1 Background on co-working

The literature provides numerous studies showing how social interactions affect the working performance of individual workers, teams, and companies; see, for instance, Hasan and Koning (2019); Chan et al. (2014). Many authors, such as (Agrawal et al., 2017; Boudreau et al., 2017; Marquis, 2003; Rosenkopf et al., 2001; Stam, 2010), suggested that proximity may drive collaboration. Being spatially close, whether in the same room or within the same geographic area, fosters the formation of social connections.

Thus, these spaces have become increasingly popular, attracting a wide range of professionals, from start-ups to freelancers, who seek an inspiring environment for their work (Lima et al., 2024).

In this model, each agent participates in at most one coalition at any given time. While professionals often collaborate across multiple teams simultaneously in reality, this assumption is justified in co-working contexts by the need to allocate specific physical resources (spaces, equipment, meeting rooms) within defined time periods. This constraint reflects the practical limitations of physical space allocation and ensures model feasibility while maintaining realistic resource management principles.

The literature has extensively discussed the benefits of co-working, including fostering emerging collaborative activity (Spinuzzi, 2012), creating a sense of community (Garrett et al., 2017), and providing social support (Howell, 2022). Co-working spaces also play a role in urban development and revitalization (Durante & Turvani, 2018), acting as third places that promote interaction (Moriset, 2013; Oldenburg, 1997) and social focus (Feld, 1981) where knowledge spreads through networks (Malecki, 2010).

The growth of co-working also aligns with the concept of open innovation, as theorized by Chesbrough (2003), which emphasizes the importance of external knowledge flows to companies. In this context, Malecki (2011) introduces the concept of double networks. Large companies, due to the lower mobility of talent compared to capital, must create external networks to capture ideas and innovative initiatives that emerge outside their research and development labs.

2 Multi-objective optimization models and its evolution

In the realm of optimization, both multi-objective optimization (MOO) models and evolutionary algorithms are widely used to solve complex problems. Evolutionary algorithms excel at navigating large search spaces and generating diverse solutions, but often demand significant computational power and may converge to suboptimal results. MOO methods (Caramia & Dell'Olmo, 2020; Deb et al., 2016; Giagkiozis & Fleming, 2015; Gunantara, 2018), on the other hand, are critical for addressing scenarios where conflicting objectives must be balanced. These models provide decision-makers with optimal trade-offs, typically represented by Pareto frontiers, where improvements in one objective cannot be made without compromising another.

MOO models are particularly effective for real-world scenarios where decision-makers must balance competing goals, such as maximizing benefits while minimizing costs. Different methodologies exist to address the trade-off between objectives in MOO. Pareto-based approaches aim to generate a set of solutions that collectively represent the trade-offs among objectives, enabling the visualization of the Pareto frontier. In contrast, scalarization methods, such as weighted-sum optimization, combine objectives into a single aggregate objective using a set of predefined weights. These weights reflect the relative importance of each objective, producing a single solution that balances the trade-offs according to the specified priorities.

No direct applications of MOO methods to co-working networks have been identified in the literature. However, similar methodologies have been successfully applied in other domains, such as healthcare, resource allocation management, and public administration. Lucidi et al. (2016) proposes a simulation-based multi-objective optimization approach for hospital resource allocation. In public administration, Arbolino et al. (2021) introduces a multi-objective optimization technique for tourism sustainability planning. Marden and Roughgarden (2014) explore efficiency limits in distributed resource allocation through game theory. In Zafari et al. (2018), a cooperative game-theoretic framework for resource sharing in mobile edge computing is proposed. Finally, in Kyriazi et al. (2017), the authors develop a cooperative game-theoretic framework to negotiate marine spatial allocation among heterogeneous players.

Despite these valuable contributions, significant limitations remain in the existing literature. First, most MOO applications in network contexts adopt static objective weights, failing to capture the evolving priorities of public decision-makers (Marler & Arora, 2010). Second, the use of the Shapley Value in optimization frameworks is typically confined to post-hoc value allocation rather than integrated into the optimization process itself (Fatima et al., 2008). Third, computational constraints have traditionally limited Shapley-based methods to small-scale networks, hindering their applicability to real-world territorial systems (Castro et al., 2009). Fourth, few studies address the seasonal and temporal dynamics that characterize collaborative environments, particularly in tourism-dependent regions. Our framework addresses these gaps by: (i) introducing dynamic λ adjustment based on real-time Shapley Values, (ii) employing computationally efficient approximation algorithms that scale to networks of 150+ agents, and (iii) incorporating seasonal modulation factors that reflect the temporal heterogeneity of co-working demand.

The relevance of MOO in the creation of co-working networks stems from the inherent complexity of these environments. Co-working spaces are shared workspaces that foster collaboration, innovation, and community-building among a diverse array of professionals. Despite their increasing prevalence, the management of co-working networks involves navigating a delicate balance between collaboration-driven value creation and operational sustainability.

In the context of co-working networks, the application of MOO offers a structured approach. It helps managers make informed choices that account for a range of critical variables. These variables influence both the success and the sustainability of the co-working environment. By integrating factors such as resource allocation, spatial optimization, community engagement, and environmental sustainability, this approach enables a balanced assessment of trade-offs and synergies. Despite the widespread use of MOO models in network design, most studies do not account for the temporal evolution of decision-making preferences nor the interaction between economic efficiency and collaborative value. Moreover, existing models tend to describe the trade-off between objectives without providing tools that allow decision-makers to adjust these priorities according to changing operational or strategic conditions. The presence of these limitations highlights the need for a more flexible framework, which the present study addresses by introducing a dynamic policy parameter (λ within the bi-objective formulation.

3 Theoretical framework for Co-working network optimization

This section introduces the theoretical foundations of our co-working network model. We first recall key concepts from cooperative game theory, focusing on coalition formation and value allocation. We then discuss the implications of network complexity for public decision-making and the need for advanced optimization tools.

3.1 Cooperative game theory foundation

Cooperative game theory provides the mathematical framework for modeling coalition formation in co-working networks. The theory examines situations where players (agents) can form binding agreements and coalitions to achieve outcomes superior to those obtainable through individual action.

Let $N = \{1, 2, ..., n\}$ be the set of agents in the co-working network. A coalition $S \subseteq N$ represents a group of agents who decide to collaborate. The characteristic function $V : 2^N \to \mathbb{R}$ assigns a value $V(S)$ to each coalition S, representing the total benefit that coalition members can achieve through collaboration.

For our co-working network model, we assume the characteristic function satisfies super-additivity:

$$V(S_1) + V(S_2) \leq V(S_1 \cup S_2) \tag{1}$$

for all disjoint coalitions $S_1, S_2 \subseteq N$ with $S_1 \cap S_2 = \emptyset$.

This property ensures that merging coalitions never decreases total value, reflecting the synergistic benefits of collaboration in co-working environments. However, this property must be verified empirically or theoretically for specific coalition value functions, as it is not automatically guaranteed in all contexts.

3.2 Network complexity in co-working ecosystems

The coalition formation problem in co-working networks represents a complex, multi-dimensional optimization challenge with computational complexity of $O(2^n)$ for n agents. This exponential growth in the number of possible coalitions necessitates sophisticated solution approaches that balance computational tractability with solution quality.

The multi-dimensional nature arises from the simultaneous consideration of collaborative value, operational costs, resource constraints, and territorial development objectives. Public decision-makers must navigate these competing dimensions while ensuring that the resulting network configuration aligns with broader policy goals, including economic development, social inclusion, and environmental sustainability.

The complexity stems from several interconnected factors:

- The discrete nature of coalition membership decisions creates a combinatorial explosion as the number of possible coalition structures grows exponentially with the number of agents.
- The multi-objective nature requires finding solutions that represent optimal trade-offs between collaborative value maximization and operational cost minimization.
- The presence of multiple resource types with different characteristics and constraints adds additional dimensions to the feasible solution space.

A coalition's value may depend on several factors, such as the diversity of skills, efficient resource utilization, the potential for collaboration among agents, and scalability to adapt to challenges. It is orthogonal to this work, studying how to form good coalitions. Many works in the literature tackle this topic (see, e.g., Kahan and Rapoport (2014); Ray and Vohra (2015); Mahdiraji et al. (2021)) and can provide a basis for computing a coalition's collective value by considering specific features.

4 A bi-objective optimization model for a network of co-working spaces

The proposed model builds upon our proposal in Alderighi et al. (2024), which uses a game-theoretic approach to examine how a Network of Co-working Spaces (NCS) can act as a catalyst for collaboration and cooperation, promoting community well-being and the local economy. The model is based on the idea of cooperation among various agents (professionals, start-ups, public entities, etc.) within an NCS, with the goal of maximizing the value generated through collaboration. Additionally, agents involved in the NCS can form coalitions to work on projects or share resources.

This work proposes an integrated model that not only optimizes coalition formation based on each agent's contribution value but also ensures that these coalitions respect limited resource constraints. The model maximizes collaborative synergies without compromising economic sustainability or fair resource distribution.

Therefore, this integrated approach enables informed decision-making by providing a holistic view that accounts for both the benefits of collaboration and the practical constraints of the network.

This study develops a bi-objective optimization model that provides a comprehensive blue decision framework for managing a co-working network. The model jointly considers the potential for collaboration and operational costs, while ensuring fairness and efficient use of available resources.

4.1 Objective functions

First, the formulas that capture the model's objectives are reported and explained. To maximize collaborative value, the value of collaboration is given by Equation 2.

$$\max \sum_{S \subseteq N} V(S) \cdot x_S \tag{2}$$

Value $V(S)$ represents the benefit derived from collaboration among the agents in coalition S. The binary variable x_S indicates whether coalition S is selected (value 1) or not (0).

As concerns the minimization of operational costs, Equation 3 aims to minimize the operational costs associated with the agents included in the coalitions.

$$\min \sum_{i \in N} c_i \cdot y_i \tag{3}$$

where c_i is the operational cost associated with agent i and y_i is a binary variable indicating whether the agent is included in a coalition (value 1) or not (0).

The objectives are combined into a single objective function using a weighting, allowing us to obtain a solution that represents a trade-off between the various criteria. The weighting parameter is denoted by λ. Thus, by combining Equations 2 and 3 mathematically:

$$\max \quad \lambda \cdot \sum_{S \subseteq N} V(S) \cdot x_S - (1-\lambda) \cdot \sum_{i \in N} c_i \cdot y_i, \text{ where } \lambda \in [0, 1] \tag{4}$$

When $\lambda = 1$, the model focuses solely on maximizing coalition value, whereas when $\lambda = 0$, it focuses exclusively on minimizing operational costs. Otherwise, the model will balance the two objectives according to the weights.

4.2 Decision-support mechanism for selecting the policy parameter *λ*

Unlike purely algorithmic approaches, our framework explicitly acknowledges that the weighting parameter λ must be defined by public decision-makers according to territorial development priorities. In practice, local and regional administrations set λ by evaluating factors such as: (i) territorial fragility and environmental sustainability constraints, (ii) economic development goals, (iii) social cohesion and inclusion objectives, and (iv) the long-term strategic vision of the region. In this sense, λ becomes a concrete public policy lever that embeds collective priorities into the optimization process, rather than a purely technical modeling parameter.

However, to support practitioners in selecting a suitable value of λ, a precise and reproducible decision-support mechanism is required. For this reason, we introduce a three-step procedure that guides policy-makers in translating contextual assessments into an operational choice of λ.

Step 1: Identification of the primary objective. The decision-maker determines whether the policy goal prioritizes (a) cost containment, (b) a balanced trade-off between efficiency and collaborative value creation, or (c) innovation-oriented growth and qualitative development.

Step 2: Assessment of territorial constraints. The public administration evaluates binding constraints such as budget availability, environmental limits, infrastructural capacity, and territorial fragility. These elements restrict the feasible policy space and guide the interpretation of λ.

Step 3: Mapping to a policy regime and corresponding* λ *range. By combining strategic objectives and contextual constraints, the policy-maker selects one of the following regimes, each associated with a recommended interval of λ:

- Resource-constrained context: when financial or environmental constraints are tight, and the priority is service continuity, the recommended range is $\lambda \in [0.0, 0.3]$ (strong emphasis on cost minimization).
- Balanced development: when both cost efficiency and collaborative value are relevant, and constraints are moderate, the suggested range is $\lambda \in [0.4, 0.6]$ (balanced weighting).
- Innovation-oriented growth: when the priority is to foster innovation, strengthen collaboration, attract knowledge workers, and stimulate qualitative development, the appropriate interval is $\lambda \in [0.7, 1.0]$ (emphasis on value creation).

This procedure is summarized in the decision scheme shown in Figure 1, which translates strategic and contextual considerations into a transparent and operational choice of λ. In practical terms, the analyst first identifies the relevant policy regime and then performs a local sensitivity analysis within the corresponding λ interval to fine-tune the final value.

Through this mechanism, λ becomes a structured, actionable instrument that explicitly encodes public policy priorities in the bi-objective optimization process.

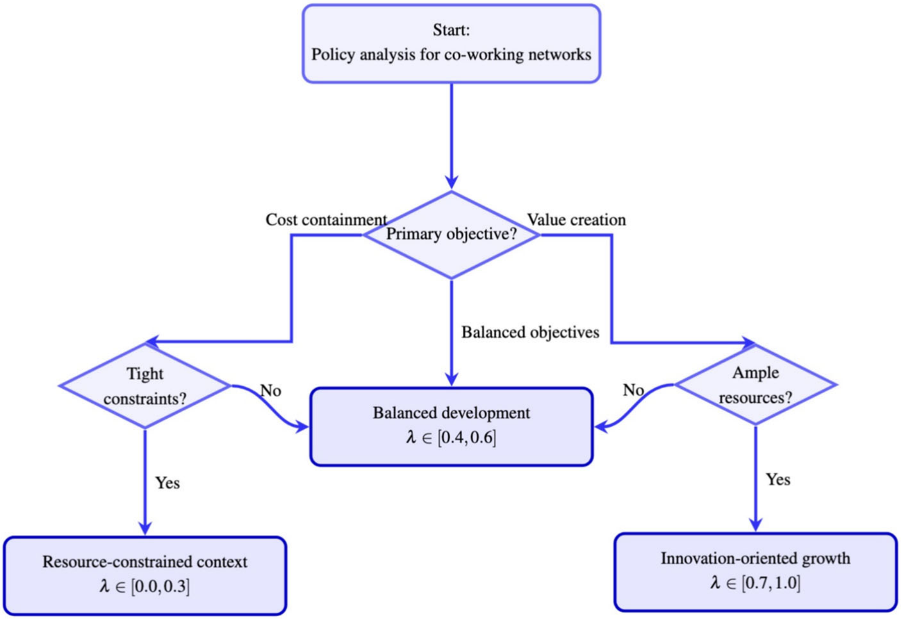

Fig. 1 Decision-support tree for selecting the policy parameter λ based on strategic objectives and territorial constraints

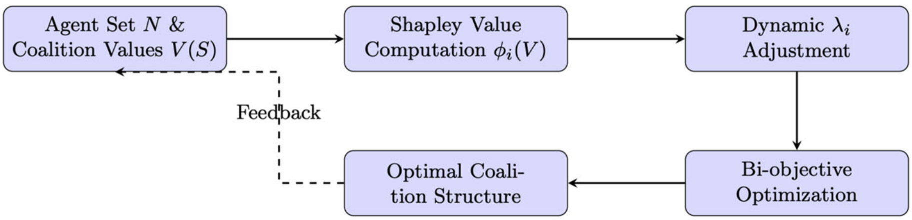

Fig. 2 Decision-support tree for selecting the policy parameter λ based on strategic objectives and territorial constraints

4.3 Introducing the dynamic adjustment of the λ parameter by Shapley Value

Figure 2 illustrates the conceptual relationship between the Shapley Value computation and the bi-objective optimization model. The framework operates through an iterative feedback loop: coalition values inform Shapley Value calculations, which in turn determine agent-specific weights (λ_i) that guide the optimization process.

The parameter λ is considered as the "filter" that determines the balance between the objectives. It allows us to adjust the relative importance of maximizing collaboration and minimizing operational costs according to the priorities of the co-working space network.

In Alderighi et al. (2024), the Shapley Value is used to calculate the marginal contributions of the agents (or nodes) in the coalitions of an NCS. These contributions measure the value each agent brings to the coalition, and therefore to the network as a whole (see Equation 5).

The Shapley Value uniquely satisfies four fundamental axioms in cooperative game theory:

1. **Efficiency:** The sum of all players' Shapley Values equals the total value: $\sum_{i \in N} \phi_i(V) = V(N)$.
2. **Symmetry:** If agents i and j contribute equally to all coalitions, then $\phi_i(V) = \phi_j(V)$.
3. **Null player:** If agent i contributes nothing to any coalition, then $\phi_i(V) = 0$.
4. **Additivity:** For two games with value functions V and W: $\phi_i(V + W) = \phi_i(V) + \phi_i(W)$.

These properties ensure that the Shapley Value provides a fair and unique solution for distributing the total value among agents based on their marginal contributions.

$$\phi_i\ (Val) = \sum_{S \subseteq N \setminus i} \frac{|S|! \cdot (n - |S| - 1)!}{n!} \left[Val\ (S\ \cup\ i)\ -\ Val\ (S)\right] \tag{5}$$

Algorithm 1 Shapley Value Approximation

Require: Coalition value function V, agent set N, sample size k
Ensure: Approximate Shapley Values ϕ

for each agent $i \in N$ **do**
    Initialize $\phi_i \leftarrow 0$
    for $j = 1$ to k **do**
        Sample random coalition $S \subseteq N \setminus \{i\}$
        $\phi_i \leftarrow \phi_i + [V(S \cup \{i\}) - V(S)]/k$
    end for
end for
return ϕ

In the proposed integrated model, the marginal contributions are used to adjust the parameter λ dynamically. This approach recognizes that the importance of collaborative value varies with each agent's role and influence in the network.

Remark 1 In recent years, the application of Shapley Values to optimization problems has expanded significantly across multiple domains. In Ciano et al. (2024), a disruptive study was conducted in the framework of the Co-Working Dynamics in the Aosta Valley using the SHAP approach for ML problems. This is one of the first analyses in this fruitful field of study.

To allow the weighting parameter λ to be dynamically adjusted, based on the Shapley Value of each agent i, λ is expressed as a function of the Shapley Value of agent i (see Eq. 6).

$$\lambda_i = f(\phi_i(V)) \tag{6}$$

where $f(\cdot)$ is a function that maps the Shapley Value $\phi_i(V)$ to a range between 0 and 1.

Therefore, the coalition values obtained via the Shapley Values are used as inputs to the objective function of the bi-objective optimization model. At this point, the overall objective function becomes:

$$\max\ \lambda_i \cdot \sum_{S \subseteq N} V(S) \cdot x_S - (1 - \lambda_i) \cdot \sum_{i \in N} c_i \cdot y_i \tag{7}$$

where λ_i is a dynamic value that depends on the marginal contribution of each agent i, calculated through the Shapley Value.

λ_i is normalized so that the total weighting value remains between 0 and 1:

$$\lambda_i = \frac{\phi_i(V)}{\sum_{j \in N} \phi_j(V)} \tag{8}$$

4.4 Multi-objective approach: motivations and a comparison with the classical net present value approach

In the context of public policy modeling, a scientific and methodological question may arise naturally: why adopt a multi-objective approach rather than simply optimizing Net Present Value (NPV)? The answer lies in the inherent complexity of public decision-making processes, which differ significantly from private optimization and require a more nuanced integration of criteria.

First and foremost, one must consider the presence of territorial externalities. The costs represented in the model do not merely reflect direct economic expenditures, but also broader territorial impacts such as environmental sustainability and land use. These externalities are often challenging to monetize and cannot be fully captured through a standard NPV calculation.

Secondly, the multi-objective approach provides greater policy flexibility. Public decision-makers operate within dynamic and evolving contexts, where priorities may shift based on territorial conditions, political agendas, and stakeholder needs.

Another key benefit of the multi-objective framework lies in its ability to enhance transparency for stakeholders. By explicitly separating the collaborative value generated from the associated costs, the model makes trade-offs more visible and understandable.

Finally, the approach allows for better integration of environmental and social dimensions. Many relevant impacts—such as pollution, biodiversity loss, or social cohesion—constitute negative externalities that are ideally internalized but often escape traditional economic evaluation tools.

4.5 Coalition selection and cooperation constraints

The coalition selection constraint ensures that, if a coalition S is selected, all agents in S must be included.

$$x_S \leq y_i \quad \forall i \in S, \forall S \subseteq N \tag{9}$$

Non-overlapping coalition constraint: To ensure that each agent can participate in at most one coalition at any given time, we introduce a non-overlapping constraint:

$$\sum_{S:i \in S} x_S \leq 1 \quad \forall i \in N \tag{10}$$

This constraint prevents agents from being simultaneously assigned to multiple coalitions, which would be physically impossible and could lead to resource conflicts.

Specific application scenarios might be characterized by the fact that collaborations are meaningful only if their cardinality respects certain limits. This is captured by the collaboration capacity constraint, expressed in Equation 11.

$$n_{min} \leq \sum_{i \in S} y_i \leq n_{max} \quad \forall S \subseteq N \text{ with } x_S = 1 \tag{11}$$

where n_{min} (lower bound) is the minimum number of participants that a coalition must have and n_{max} (upper bound) is the maximum number of participants a coalition can have.

4.6 Superadditivity constraint

The superadditivity constraint of coalitions, expressed by Equation 12, is an important condition in an optimization model that involves advantageous cooperation between agents.

$$V(S_1) + V(S_2) \leq V(S_1 \cup S_2) \quad \forall S_1, S_2 \in P(N) \text{ and } S_1 \cap S_2 = \emptyset \tag{12}$$

This constraint ensures that merging coalitions produces a value at least as large as the sum of the separate coalitions. This property must be verified empirically for each specific context, as it is not guaranteed in all co-working environments.

4.6.1 Numerical example in the co-working context

Consider three professionals in a co-working network:

- **A**: a freelance graphic designer
- **B**: a digital marketing consultant
- **C**: a web developer

Coalition values are assigned based on skill complementarity:

$$\begin{aligned} V(\{A\}) &= 100, & V(\{B\}) &= 120, & V(\{C\}) &= 110 \\ V(\{A, B\}) &= 250, & V(\{A, C\}) &= 240, & V(\{B, C\}) &= 260 \\ V(\{A, B, C\}) &= 400 \end{aligned}$$

Let us verify the **superadditivity** property:

- $V(\{A\}) + V(\{B\}) = 220 \leq V(\{A, B\}) = 250$
- $V(\{A, B\}) + V(\{C\}) = 360 \leq V(\{A, B, C\}) = 400$

4.6.2 Limitations of superadditivity

While the superadditivity assumption generally holds in co-working contexts, several factors may undermine its validity. Large coalitions, for instance, can incur significant coordination costs due to communication overhead, thereby reducing overall efficiency. Moreover, cultural conflicts arising from heterogeneous working styles and organizational norms can generate friction that limits collaborative performance. Competition for shared resources can also create operational bottlenecks, particularly when demand exceeds available capacity. Finally, the simultaneous participation of agents in multiple projects may dilute focus, diminishing individual productivity and collective outcomes. In practice, the superadditivity property should therefore be empirically verified for each specific context. Future developments should incorporate coalition-specific cost functions to capture potential inefficiencies more accurately.

4.7 Transportation constraint

The transportation constraint limits travel costs between coalition members based on geographic distance. This constraint seeks to limit transportation costs between the agents of a coalition, taking into account the geographical distance between these agents. This situation is described in Equation 13:

$$\sum_{i \in S, j \in S} d_{ij} \cdot c_T \leq \overline{T} \quad \forall S \subseteq N \tag{13}$$

where d_{ij} is the distance between nodes i and j, c_T is the unit transportation cost per unit of distance, and $\overline{T}$ is the maximum transportation cost that a coalition can afford.

4.8 Resource constraints

Resource constraints reflect the practical limitations that public managers face when operating co-working networks. Given the heterogeneous nature of resources in co-working environments, we extend the basic resource constraint to accommodate multiple resource types. Let R be the set of all resource types, and let $r_{i,k}$ represent the amount of resource type $k \in R$ required by agent i. The multi-resource constraint is described by:

$$\sum_{S \subseteq N} \sum_{i \in S} r_{i,k} \cdot x_S \leq TR_k \quad \forall k \in R \tag{14}$$

where $r_{i,k}$ is the amount of resource of type k required by agent i and TR_k is the maximum limit of resource type k available globally.

4.9 Specific resource constraints

The space constraint ensures that the sum of the space required by the agents in a coalition does not exceed the total available space TS:

$$\sum_{S \subseteq N} \sum_{i \in S} s_i \cdot x_S \leq TS \tag{15}$$

The funding constraint ensures that the sum of the funding requested by the agents of selected coalitions does not exceed the total available funding TF:

$$\sum_{S \subseteq N} \sum_{i \in S} f_i \cdot x_S \leq TF \tag{16}$$

The time constraint ensures that the sum of the time required by selected coalitions does not exceed the total available time TT:

$$\sum_{S \subseteq N} \sum_{i \in S} t_i \cdot x_S \leq TT \tag{17}$$

To ensure equity and inclusive participation within the co-working network, we introduce an equity constraint. Let e_i denote the equity score associated with agent i. The equity constraint ensures that the total equity contribution from selected coalitions reaches at least a minimum threshold $TE_{\min}$:

$$\sum_{S \subseteq N} \sum_{i \in S} e_i \cdot x_S \geq TE_{\min} \tag{18}$$

4.10 Additional constraints

Minimum coalition viability constraint. To ensure that selected coalitions generate sufficient value to justify their operational costs, we introduce a minimum viability threshold:

$$V(S) \cdot x_S \geq V_{min} \cdot x_S \quad \forall S \subseteq N \tag{19}$$

Capacity utilization constraint. To promote efficient use of co-working facilities, we introduce a constraint that ensures minimum utilization levels:

$$\sum_{S \subseteq N} \sum_{i \in S} s_i \cdot x_S \geq \alpha \cdot TS \tag{20}$$

where $\alpha \in (0, 1]$ represents the minimum utilization rate required for the co-working network.

4.11 Decision variables

In Equations 21-24, the nature of the proposed model decision variables is described:

$$x_S \in \{0, 1\} \quad \forall S \subseteq N \tag{21}$$

$$y_i \in \{0, 1\} \quad \forall i \in N \tag{22}$$

$$x_{iS} \in \{0, 1\} \quad \forall i \in S, \forall S \subseteq N \tag{23}$$

$$r_{i,k}, s_i, t_i, f_i, e_i \geq 0 \quad \forall i \in N, \forall k \in R \tag{24}$$

5 Optimal resource allocation under dynamic coalition formation

This section presents the theoretical foundations for optimal resource allocation under dynamic coalition formation. We first define Pareto efficiency and then state our main result.

A solution is considered Pareto efficient (or Pareto optimal) if it is impossible to improve one objective without deteriorating at least one other objective. In our bi-objective framework, a coalition structure is Pareto efficient if we cannot simultaneously increase the collaborative value and decrease the operational costs, or vice versa.

More formally, given two solutions S_1 and S_2 with collaborative values V_1, V_2 and operational costs C_1, C_2 respectively, solution S_1 Pareto dominates S_2 if:

- $V_1 \geq V_2$ and $C_1 \leq C_2$ (at least as good in both objectives)
- At least one inequality is strict (strictly better in at least one objective)

Theorem 1 (Optimal resource allocation under dynamic coalition formation)*] Let N be a set of agents in a co-working network, $V(S)$ be the value of coalition $S \subseteq N$, and $\phi_i(V)$ be the Shapley Value of agent i. For each $i \in N$, let c_i be the operational cost, and r_i be the resource requirement of agent i.*

Assume resource constraints of the form $\sum_{i \in S} r_i \leq T_R$ for all $S \subseteq N$. If the weighting parameter $\lambda_i = \frac{\phi_i(V)}{\sum_{j \in N} \phi_j(V)}$ is dynamically adjusted based on agent Shapley Values, then the optimal solution to the bi-objective problem:

$$\max \lambda_i \cdot \sum_{S \subseteq N} V(S) \cdot x_S - (1 - \lambda_i) \cdot \sum_{i \in N} c_i \cdot y_i \tag{25}$$

subject to coalition selection constraint $x_S \leq y_i$ for all $i \in S, S \subseteq N$, guarantees a Pareto-efficient allocation. This allocation converges to a stable coalition structure as the number of iterations increases.

Proof We prove this theorem by induction on the number of agents $n = |N|$. For $n = 1$, the result is trivial. Assuming the theorem holds for all sets of agents of size $k < n$, consider a set N of size n. The dynamic adjustment of λ_i based on Shapley Values ensures that agents with higher marginal contributions have greater influence on the objective function. The allocation converges to a stable solution because any deviation would decrease the objective function value. □

Proposition 2 *In a co-working network with resource constraints, if resources are allocated proportionally to the normalized Shapley Values of agents, then the resulting allocation maximizes the expected collaborative value while ensuring equity in resource distribution.*

6 Co-working space location strategies: the case study of the Aosta Valley

This analysis is based on real demographic and geographic data obtained from official sources, including ISTAT (Italian National Institute of Statistics) and the Regional Geographic Information System of Aosta Valley. All population distribution data, economic indicators, and infrastructure information used in our model come from verified governmental sources. We assume that the locations of co-working participants, both within the Aosta Valley and from other regions, follow the geographic distribution of the resident population. This assumption aligns with technical aspects of many current public policies in this domain. It is justified by the fact that larger urban centers offer more services - such as schools, hospitals, supermarkets, and transportation infrastructure - which naturally attract external professionals.

The Aosta Valley has approximately 123,000 inhabitants spread across 74 municipalities. Among them, only the regional capital Aosta exceeds 10,000 residents, with a population of around 33,000. About 75% of the population is concentrated in the 28 municipalities located in the non-mountainous central valley, while the remaining 25% resides in mountainous areas.

From this distribution, we assume that the location of remote workers follows the same pattern: 75% are directed to central areas, and 25% to mountain zones. This assumption is fundamental to our spatial analysis and is supported by theoretical frameworks drawn from urban economics and tourism geography.

6.1 Seasonal dynamics in mountain co-working networks

The Aosta Valley exhibits pronounced seasonal fluctuations in economic activity due to its strong dependence on tourism. The winter months (December–March) generate peak inflows associated with ski tourism, while summer (July–August) attracts large numbers of visitors for hiking and outdoor recreation. These dynamics directly affect co-working space utilization and the formation of collaborative opportunities.

In particular:

– **Winter peak (Dec–Mar)**: 95-100% tourism capacity, with high demand for temporary workspaces from remote workers and digital nomads.

Table 1 Seasonal decomposition of agent utilization and collaborative value

Month	Q	Utilization (%)	Collab. Value	Coalitions	Status
January	Q1	48 ± 6	1050 ± 80	12	Baseline
February	Q1	52 ± 5	1080 ± 85	13	Low
March	Q1	58 ± 7	1120 ± 90	14	Growing
April	Q2	64 ± 7	1180 ± 90	16	Moderate
May	Q2	68 ± 8	1210 ± 95	17	Moderate
June	Q2	70 ± 8	1240 ± 100	18	Growing
July	Q3	78 ± 9	1380 ± 100	21	**Peak**
August	Q3	80 ± 10	1380 ± 105	22	**Peak**
September	Q3	76 ± 8	1350 ± 100	20	High
October	Q4	72 ± 8	1320 ± 95	19	Declining
November	Q4	65 ± 7	1250 ± 90	16	Moderate
December	Q4	58 ± 6	1180 ± 85	14	Low

Values represent mean ± 95% confidence interval. Peak season in Q3 shows 60% higher utilization compared to Q1 baseline

- **Summer high (Jul–Aug)**: 85-90% capacity, supported by steady inflows of outdoor-oriented professionals.
- **Shoulder seasons (Apr–Jun, Sep–Nov)**: 40-60% capacity, representing opportunities for resident professionals and long-term collaborations.

To incorporate these temporal variations into the optimization model, we introduce a seasonality factor:

$$F_{\text{seas}} = 1 + \alpha \cdot \cos(2\pi t/T), \quad (26)$$

where $\alpha = 0.3$ represents the amplitude of demand fluctuations and $T = 12$ months. This factor modulates the coalition value function and the resulting network configurations over time.

Furthermore, Table 1 provides a visual representation of utilization dynamics across the four seasons, highlighting the contrast between high-demand and low-demand periods and their implications for coalition formation and resource allocation.

7 Allocative efficiency in co-working networks: evidence from a Shapley-based simulation

Our analysis employs real data from the following official sources:

- Demographic data: ISTAT Census 2021 and population registry 2024 for all 74 municipalities of Aosta Valley (approximately 123,000 inhabitants)
- Geographic distribution: Regional Geographic Information System of Aosta Valley, providing detailed topographical and infrastructure mapping
- Economic indicators: Chamber of Commerce of Aosta Valley business registry, including company sizes, sectors, and employment data
- Infrastructure data: Regional transportation authority databases, including public transport networks and accessibility indices

Table 2 Resource requirements by agent type

Agent Type	Space (m^2)	Time (hrs)	Funding (€)	Equity
Freelancer	5-15	5-50	1,000-5,000	1-3
Startup	15-30	50-100	5,000-20,000	3-10
SME	30-50	100-200	10,000-30,000	5-15
Consultant	10-20	20-80	2,000-8,000	2-5

– Tourism statistics: Regional tourism observatory data for 2022-2024, showing seasonal patterns and visitor flows

The simulation combines these real datasets with optimization algorithms to determine optimal coalition configurations. Agent characteristics (freelancers, startups, SMEs, consultants) are derived from actual business registry data, ensuring realistic parameter ranges.

To validate our theoretical framework, we conducted a numerical simulation using data on the demographic characteristics of the Aosta Valley region. We modeled a network of 100 potential agents distributed across 10 co-working spaces. The agents and co-working spaces were geographically positioned using simplified two-dimensional coordinates representing the region's topography. Consistent with regional demographics, 75% of the agents and co-working spaces were located in the central valley areas, while the remaining 25% were distributed across mountain municipalities.

The agents were divided into four categories: freelancers (50%), startups (30%), SMEs (10%), and consultants (10%). Each agent was assigned a random skill score across six domains (Technology, Design, Business, Marketing, Finance, and Legal) to model collaborative potential based on complementary skills (See Table 2).

The simulation was implemented using Python 3.8. Regarding computing resources, the system was tested on machines equipped with multi-core CPUs and 8 to 16 GB of RAM. The full simulations took approximately 45–60 minutes to complete.

8 Coalition valuation and network optimization under constraints

For assessing the collaborative potential within the co-working network, we developed a coalition evaluation function that integrates both structural and contextual dimensions. The coalition evaluation function combines multiple value dimensions through a multiplicative structure. While the seasonality factor F_{seas} is explicitly formalized in Equation 26, the remaining component functions are described below.

Coalition size value (V_{size})

The base value of a coalition is modeled as a function of its cardinality, reflecting the principle that larger teams generate greater potential value through increased resource pooling and diversity of perspectives:

$$V_{\text{size}}(S) = \beta_1 \cdot |S|^{\gamma} \tag{27}$$

where β_1 is a scale parameter calibrated to the specific territorial context, $|S|$ denotes the number of agents in coalition S, and $\gamma \in (0, 1]$ is an elasticity parameter. The choice $\gamma < 1$ captures diminishing marginal returns to coalition size, reflecting coordination overhead and communication costs identified in the literature (Hackman & Vidmar, 1970; Lakey & Cohen, 2000; Mueller, 2012). When $\gamma = 1$, the relationship is linear.

Skill complementarity value ($V_{\mathbf{comp}}$)

Complementarity is quantified through the diversity of expertise domains represented within the coalition.

Let $K = \{\text{technology, design, business, marketing, finance, legal}\}$ represent the k domains, and let $\text{skill}_{i,k} \in [0, 1]$ denote the proficiency level of agent i in domain k. Complementarity is measured as:

$$V_{\text{comp}}(S) = \beta_2 \cdot \frac{1}{|K|} \sum_{k \in K} \left(1 - \prod_{i \in S} (1 - \text{skill}_{i,k}) \right) \tag{28}$$

This formulation captures the probability that at least one coalition member possesses meaningful competence in each domain. The value ranges from 0 (no coverage) to β_2 (full coverage across all domains). The normalization by $|K|$ ensures scale independence from the number of skill domains considered.

Expertise breadth value ($V_{\mathbf{exp}}$)

Beyond complementarity, coalitions benefit from the breadth of domain coverage. Let $D(S) \subseteq K$ denote the set of domains in which at least one coalition member has proficiency exceeding a threshold $\tau_{\text{skill}} \in (0, 1]$:

$$V_{\text{exp}}(S) = \beta_3 \cdot \frac{|D(S)|}{|K|} \tag{29}$$

This metric rewards coalitions with multidisciplinary capabilities. While conceptually related to V_{comp}, V_{exp} captures the *number of domains with meaningful coverage*, whereas V_{comp} captures the *strength of that coverage*. The normalization by $|K|$ yields a value in $[0, \beta_3]$.

Geographic dispersion penalty ($F_{\mathbf{trans}}$)

Transportation constraints (Equation (13)) limit coalition viability based on cumulative distance. The transportation factor penalizes geographic dispersion, following an exponential decay model:

$$F_{\text{trans}}(S) = \exp\left(-\delta \cdot \frac{\overline{d}(S)}{d_{\text{ref}}} \right) \tag{30}$$

where

$$\overline{d}(S) = \frac{1}{\frac{|S|(|S|-1)}{2}} \sum_{\substack{i,j \in S \\ i<j}} d_{ij}$$

is the mean pairwise distance within the coalition, $\delta \geq 0$ is a sensitivity parameter governing the strength of geographic friction, and d_{ref} is a reference distance (e.g., 10 km) used for normalization. When $\delta = 0$, geographic distance has no effect. Higher δ values impose stronger penalties for dispersed coalitions. The exponential form ensures that $F_{\text{trans}}(S) \in [0, 1]$, representing a proportional reduction in coalition value. Equivalently, the transportation penalty can be expressed through the feasibility constraint, in which case F_{trans} becomes a binary indicator rather than a continuous penalty. The choice between formulations depends on whether constraints are hard (infeasible coalitions excluded) or soft (feasible but penalized).

Parameter calibration and interpretation

The weighting parameters $\beta_1, \beta_2, \beta_3$ reflect the relative importance of size, complementarity, and breadth of expertise in the specific territorial context. These should be calibrated using:

– Expert elicitation from co-working space operators and regional development planners;

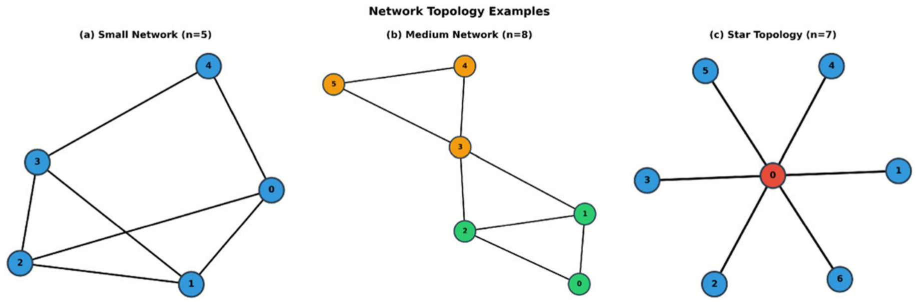

Fig. 3 Network topology and coalition formation dynamics

– Empirical data on actual coalition formations and their measured outcomes;
– Sensitivity analysis to assess robustness to parameter variations.

The skill threshold τ_{skill} and reference distance d_{ref} require contextual specification. For the Aosta Valley case study, τ_{skill} is set to 0.5 (moderate proficiency) and $d_{\text{ref}} = 10$ km, reflecting regional transportation patterns.

Aggregation structure and multiplicative properties
Therefore $V(S)$ follows a mixed aggregation logic:

$$V(S) = \left(V_{\text{size}}(S) + V_{\text{comp}}(S) + V_{\text{exp}}(S)\right) \times F_{\text{trans}}(S) \times F_{\text{seas}}(t) \tag{31}$$

This structure treats the three value components as additively separable, while geographic and seasonal factors operate multiplicatively. This reflects the assumption that:

– V_{size}, V_{comp}, and V_{exp} are independent dimensions of collaborative potential, with additive effects;
– Transportation and seasonality are *modulation factors* that reduce (or enhance) coalition viability without changing the fundamental collaborative structure.

8.1 Network topology, coalition formation, and structural dynamics

The valuation functions defined above operate within a network context whose topological properties shape coalition formation. Network topology -the pattern of connections among agents - is not independent of coalition dynamics. It determines which coalitions are feasible and which are likely to remain stable. It also influences how value is distributed among members. Understanding this interplay between network structure and coalition behavior is essential for predicting real-world outcomes and for designing interventions that account for emergent organizational properties.

The exemplary topologies in panels (a)–(c) (see Fig. 3)represent distinct organizational architectures, each with important implications for coalition formation and value realization. Panel (a) shows a small, densely connected network (n = 5) in which agents are highly interconnected. This structure allows coalitions to form flexibly across many possible membership combinations. The high connectivity supports rapid information flow and mutual monitoring. As a result, coalitions can be created based on skill complementarity and task requirements rather than spatial proximity or existing organizational boundaries. In such environments, coalition formation is dynamic and adaptive. Agents reorganize into new coalitions as project opportunities arise and conditions change. The valuation function (Equation 31) operates with minimal topological friction, since agents can combine based solely on skill match and geographic feasibility.

Panel (b) presents a medium-sized network (n = 8) with a hierarchical or community structure. Agents cluster into distinct groups (orange and green blocks) connected by only a few inter-cluster links. This architecture mirrors real organizational settings, where groups often form around shared interests, geographic proximity, or institutional affiliations. Within each cluster, coalitions form easily because agents share proximity, trust relationships, and similar institutional contexts. Inter-cluster coalitions, however, face greater friction. They require coordination across different organizational settings, often rely on broker agents to bridge communities, and are exposed to information asymmetries and weaker monitoring. In this context, the transportation penalty (F_{trans}) becomes especially important. Coalitions that span clusters incur higher average distances and therefore lower viability. This dynamic helps explain why real co-working ecosystems tend to form coalitions at the community level rather than globally optimized grand coalitions.

Panel (c) illustrates the most centralized topology: a star structure ($n = 7$) in which a single hub agent (node 0, red) connects to all peripheral nodes. In contrast, the peripheral agents are not directly connected. This topology strongly limits coalition formation. Any viable coalition must either involve peripheral agents that all connect through the hub or be directly led by the hub itself. As a result, the hub becomes a critical bottleneck. Coalition formation cannot proceed without its participation or mediation. This dynamic creates a pronounced principal–agent problem, as the hub can appropriate a disproportionate share of coalition value. Peripheral agents have no alternative coalition pathways and, therefore, limited bargaining power. In such star networks, the Shapley Value naturally produces asymmetric allocations that favor the hub, whose marginal contribution is essential in nearly all coalitions. Policy intervention through dynamic λ adjustment becomes crucial to prevent exploitative outcomes.

For policy-makers, these dynamics highlight a key point: coalition policy cannot treat network topology as exogenous or irrelevant. Before calibrating λ or applying other coalition-level interventions, authorities must understand the existing structure - where clusters form, which agents act as bridges, and where centralization risks appear. In dense networks, policy can rely on market-driven coalition formation with minimal oversight. In clustered networks, however, policy must address coordination barriers between groups. This may require subsidies for cross-cluster coalitions or infrastructure investments that reduce the friction of moving across bridges. In centralized topologies, policy must enforce strong oversight and may need structural reforms to limit hub exploitation. A topology-sensitive approach thus replaces one-size-fits-all strategies with context-aware, structurally informed policies grounded in a detailed understanding of network architecture and its implications for feasible and sustainable coalition formation.

8.2 Computational complexity and scalability

The exact computation of the Shapley Value has complexity

$$O(2^n \cdot n^2),$$

where n is the number of agents. This cost arises from evaluating all possible coalitions and computing each agent's marginal contribution. In co-working networks with 50-200 agents, the exact method becomes infeasible.

To ensure tractability, we use a sampling-based approximation with complexity

$$O(n^3 \cdot k),$$

where k is the sample size. This approach reduces the number of required coalition evaluations while maintaining high accuracy.

Performance benchmarks on standard hardware (8-16 GB RAM, multi-core CPU) highlight this difference:

- 50 agents: 2.3 min (exact) vs. 0.5 min (sampling)
- 100 agents: 45 min vs. 8 min
- 200 agents: 3.2 h vs. 25 min
- 500 agents: not tractable (exact) vs. 1.5 h (sampling)

The approximation remains within 5% of the exact solution for networks up to 200 agents, with convergence improving as k increases. This makes it suitable for coalition evaluation and for integration into our bi-objective optimization model.

Both computational and methodological considerations support the choice of sampling. Stratified sampling ensures proportional representation of coalitions of different sizes, reduces variance, and yields stable marginal contributions. The resulting estimates are robust and efficient.

For each agent i, the Shapley Value $\phi_i(V)$ is estimated as the average marginal contribution over a representative set M_i of sampled coalitions:

$$\phi_i(V) \approx \frac{1}{|M_i|} \sum_{S \in M_i} [V(S) - V(S \setminus \{i\})] .$$

This approximation preserves all information needed to rank agents, assess coalition incentives, and guide the optimization algorithm and policy trade-offs.

Since our goal is not to compute exact monetary payoffs but to identify stable coalition structures and evaluate policy scenarios, the sampling approach is fully adequate. It provides scalability, robustness, and efficiency, especially when many Shapley computations are required in dynamic or seasonal simulations.

9 Simulation scenarios

This section presents the main results of the simulation study. To evaluate the effectiveness and adaptability of the proposed optimization model, we designed two simulation scenarios. Each scenario reflects a distinct strategic approach to resource allocation and coalition formation in the context of a co-working network.

In the first scenario (static λ approach), we adopt a conventional weighted-sum strategy. The trade-off between collaborative value and operational cost is controlled by a fixed scalar parameter λ. A series of fixed values ($\lambda = 0.2, 0.4, 0.6, 0.8$, and 1.0) is used to explore different prioritization levels along the Pareto frontier.

In the second scenario (dynamic λ adjustment), we introduce an adaptive optimization mechanism in which the λ parameter is no longer fixed but varies dynamically across agents. Specifically, λ_i is adjusted for each agent based on their normalized Shapley Value, which captures their marginal contribution to coalition value.

Table 3 Performance comparison across optimization scenarios (30 runs)

Scenario	λ	Collab. Value	Op. Cost (€)	Coalitions	Std. Dev.
Static λ	0.2	845.2 ± 42.3	56,430 ± 2,821	12	0.050
Static λ	0.4	1,210.5 ± 60.5	78,650 ± 3,932	17	0.045
Static λ	0.6	1,485.7 ± 74.3	92,845 ± 4,642	22	0.042
Static λ	0.8	1,632.1 ± 81.6	110,250 ± 5,512	24	0.038
Static λ	1.0	1,728.4 ± 86.4	124,780 ± 6,239	25	0.035
Dynamic λ	Varied	1,838.6 ± 91.9	100,520 ± 5,026	24	0.028

Values represent mean ± standard deviation from 30 independent simulation runs. The dynamic approach shows significantly better performance ($p < 0.01$, Wilcoxon signed-rank test)

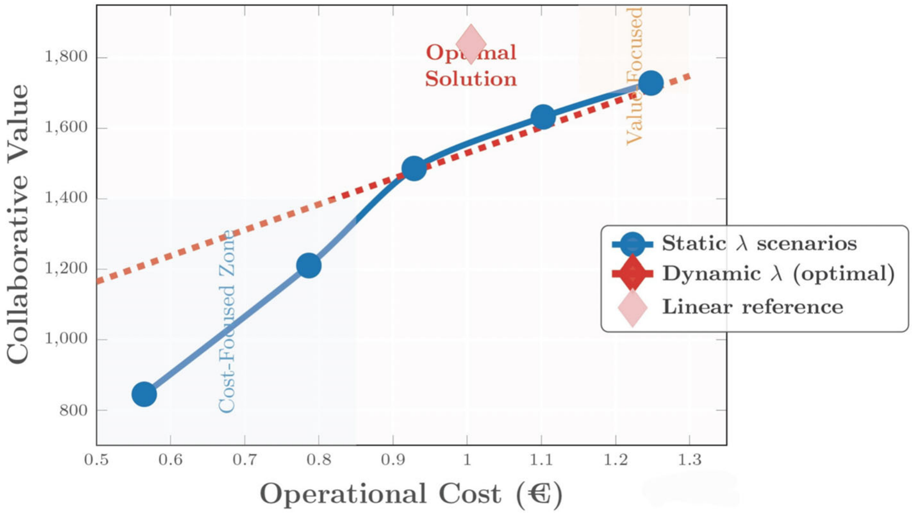

Fig. 4 Enhanced Pareto frontier showing trade-offs between collaborative value and operational costs

9.1 Comparative performance analysis

Table 3 provides a comparative overview of the key performance metrics obtained across the different optimization scenarios considered in the study.

9.2 Pareto frontier analysis

As shown in Fig. 4, the Pareto frontier illustrates the trade-off between operational cost and collaborative value across different network optimization scenarios. The circular markers represent static λ configurations. In contrast, the red diamond highlights the dynamic λ scenario, which clearly outperforms all static alternatives.

9.3 Resource utilization analysis

In Fig. 5 and Table 4 we show the agent utilization rates across the various optimization scenarios considered in the model.

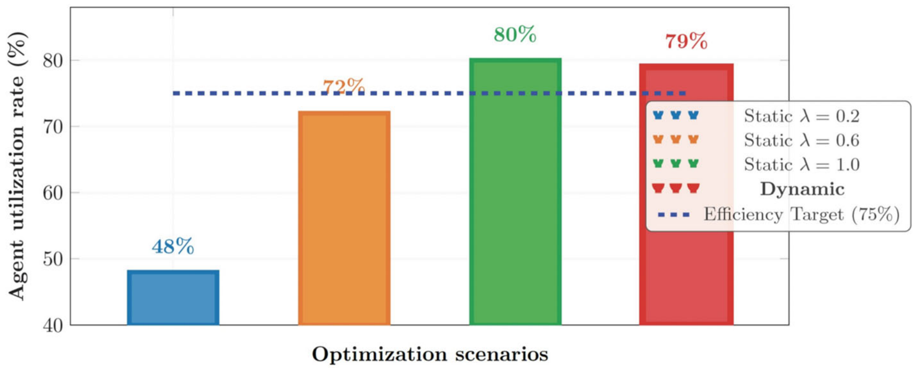

Fig. 5 Resource utilization comparison across optimization methods

Table 4 Performance summary.

Method	Utilization	Coalitions	Agents	Efficiency
Static λ = 0.2	48%	12	45	0.015
Static λ = 0.6	72%	17	58	0.015
Static λ = 1.0	80%	22	67	0.016
Dynamic	**79%**	**24**	**79**	**0.018**

9.4 Sensitivity analysis

9.4.1 Coalition size limits

We tested maximum coalition sizes of 4, 6, 8, and 10 agents:

- Size limit 4: Lower collaborative value (-18%) but faster computation.
- Size limit 6: Optimal balance (baseline)
- Size limit 8: Marginal improvement (+3%) with 2x computation time.
- Size limit 10: Diminishing returns (+4%) with 5x computation time.

The results confirm that coalition sizes above 6 agents yield diminishing returns due to coordination overhead, validating our baseline choice.

9.4.2 Parameter variations and resource constraint relaxation

The sensitivity and stability of the model were assessed through two complementary tests. First, the model's robustness was evaluated by introducing 20% variations in all parameters. The results indicated limited fluctuations in output: less than 8% for resource costs, 6% for transportation costs, 7% for space requirements, and 9% for financing constraints. These results confirm that the model remains stable and reliable under moderate parameter uncertainty. A second analysis focused on relaxing resource constraints, examining how incremental increases in available resources affect overall value creation. The results reveal a pattern of diminishing returns: a 10% increase in resources led to a 6% improvement in total value, a 20% increase produced an 11% gain, and a 30% increase produced a 14% improvement. This indicates that while additional resources improve performance, their marginal impact gradually decreases beyond a certain threshold.

9.5 Comprehensive performance analysis

The comprehensive performance analysis across all optimization scenarios is summarized in Table 3, which compares five critical dimensions: collaborative value, operational costs, utilization rates, number of coalitions formed, and efficiency ratios. The dynamic λ approach consistently outperforms all static alternatives, achieving the highest overall performance rating.

10 Public policy implications

Public policy can act directly on the weighting parameter λ through a variety of instruments, such as education and skills policies, investments in physical and digital infrastructure, administrative simplification policies, place-based and territorial development programs, cultural policies, and public-private partnership arrangements. These different policy levers do not merely influence agents' propensity to co-work. They also reshape the territorial conditions that determine whether collaboration is feasible and valuable. In doing so, they can amplify - or attenuate - the social returns that co-working networks can deliver. In short, λ is a policy-sensitive filter. Changes in infrastructure, human capital, taxation, or regulation alter both the incentives to form coalitions and the scope of their externalities. As a result, co-working produces effects that go far beyond the immediate management of shared spaces.

Operationalizing this insight, we propose five illustrative, mutually exclusive, and contiguous regimes that correspond to distinct growth objectives:

(i) Resource-constrained growth — $\lambda \in [0.00, 0.20)$: the priority is to sustain essential services and system viability under fiscal and resource constraints.
(ii) Frugal efficiency growth — $\lambda \in [0.20, 0.40)$: the aim is quality-preserving growth within tight financial boundaries.
(iii) Balanced growth — $\lambda \in [0.40, 0.60)$: a middle-ground stance that jointly pursues efficiency and collaborative value.
(iv) Inclusive growth — $\lambda \in [0.60, 0.80)$: emphasis is placed on redistributive and participatory growth.
(v) Qualitative development — $\lambda \in [0.80, 1.00]$: the focus is on the qualitative dimensions of growth, combining the accumulation of intangible assets (human, social, and cultural capitals) with selective material investments to enhance territorial performance and collective capabilities.

The five illustrative examples offered above are necessarily schematic. Within each regime, there exist varying degrees of attainment and a range of intermediate positions whose boundaries are far more porous than a discrete taxonomy suggests. However, a general implication emerges: public policy rarely presents itself as a binary choice; instead, it unfolds along a continuum of gradations and trade-offs. Employing the continuous parameter λ to map several policy regimes brings this model within the policy-mix literature. Indeed, by reframing public interventions not as isolated instruments but as positions along a continuum in which trade-offs are intrinsic, this perspective clarifies why it is challenging to pursue compound policy objectives simultaneously. It also highlights the inherent complexity involved in combining and balancing distinct policy levers.

Moreover, the paper's dynamic adjustment mechanism offers a substantive contribution to the public management literature on innovation ecosystems. By aligning optimization parameters with territorial and societal goals, the mechanism moves the discussion beyond narrow efficiency metrics and towards a bi-objective public calculus that explicitly accounts for territorial externalities. Empirically, the dynamic approach proves effective in the Aosta Valley case. It achieves 12.7% higher collaborative value while reducing operational costs by 8.8% relative to the best static alternative. This finding reinforces the theoretical premise that public-guided dynamic weighting can deliver both greater value and lower costs.

The two mechanisms studied can also be interpreted in normative terms as a contrast between a fixed-weight (static) regime and a performance-contingent (dynamic) regime. In the static case, λ is chosen uniformly, whereas in the dynamic case, λ varies according to agents' marginal contributions, effectively rewarding higher performers and enabling differential support. This differentiation partly explains the superior performance of the dynamic approach. By privileging agents or coalitions with demonstrable marginal contributions, the policy allocates scarce public resources where they yield the most significant collaborative return.

Finally, framing the static model as primarily top-down and the dynamic model as a hybrid top-down and bottom-up approach provides an additional explanation for the dynamic model's superiority. It also conveys a key lesson for policy-makers: the centrality of data and information. Successful implementation relies on timely, high-quality data on agent characteristics and local conditions, as well as on administrative and operational structures that are close to citizens. Local public bodies must therefore be equipped not only with funding but also with robust information systems and analytical capacity, enabling bottom-up signals to guide public interventions. In this context, enhanced collaboration between the public and private sectors can also play a key role.

Together, these insights suggest a practical agenda for policy-makers. First, they should map a continuum of potential public outcomes and tailor policy instruments accordingly. Second, they should adopt public-private arrangements and mixed public instruments; incorporate decentralized mechanisms that reward performance. Finally, they should invest in local data and administrative capacity. This approach allows authorities to leverage co-working networks for territorial development while explicitly acknowledging the complexity and trade-offs inherent in real-world policy mixes.

The seasonal and convergence analysis reveals critical patterns underlying co-working dynamics. Panel (a) of figure 6 shows the distribution of Shapley Values in the three regimes of λ, highlighting that $\lambda = 0,2$ produces the most uniform distribution, $\lambda = 0,6$ an intermediate profile, and $\lambda = 1.0$ the most significant concentration, with very high values for a few agents and almost zero for the others. Overall, as λ increases, the collaborative value tends to polarize, while lower values favor greater allocative equity. Panel (b) traces convergence dynamics for representative agents, showing that contribution patterns stabilize reliably after approximately 300 sampling iterations, confirming the robustness of the computational approach. Most significantly, panels (c) and (d) reveal strong seasonal effects that challenge static policy assumptions. Utilization rises from 50% in Q1 to 77% in Q3, while collaborative value shows an even larger shift, reaching 1380 in Q3 compared to a Q1 baseline of 1050 - a 60% efficiency premium during peak season. This seasonal volatility underscores why dynamic policy calibration is imperative - fixed policy weights cannot capture the temporal heterogeneity that characterizes real-world co-working networks.

The agent–λ interaction heatmaps reveal the fine-grained sensitivity of co-working outcomes to policy parameters and agent heterogeneity (Figure 7). The left panel maps Shapley Value sensitivity across the full λ range (0.2–1.0) for all 10 agents. It shows a monotonic

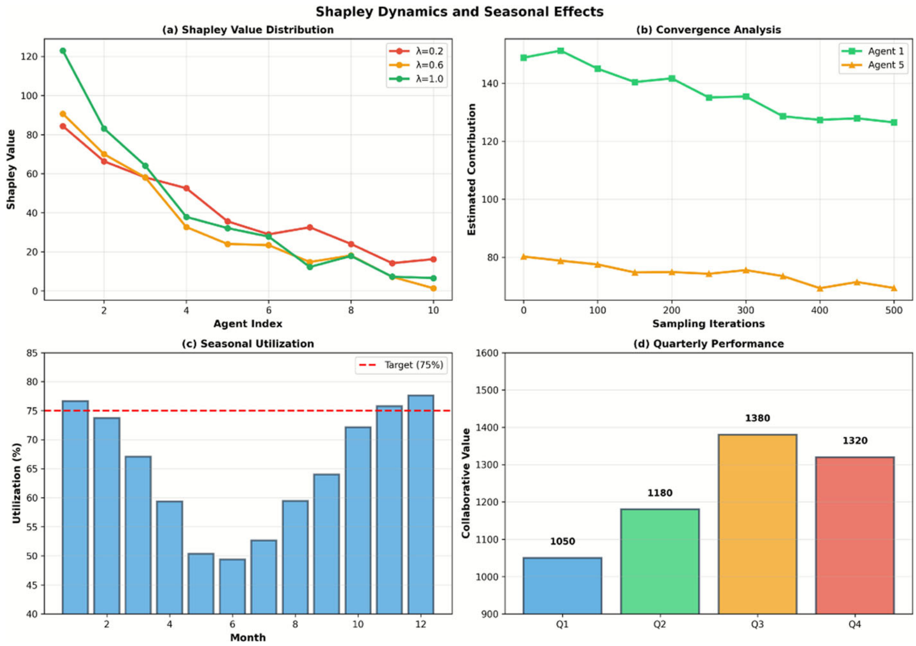

Fig. 6 Detailed seasonal analysis and convergence behavior

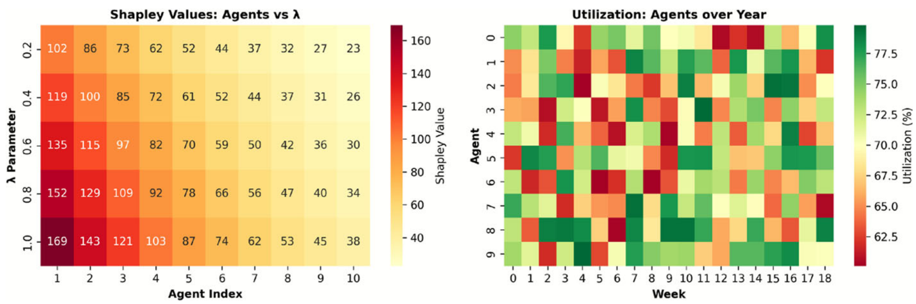

Fig. 7 Agent-λ interaction patterns and utilization heterogeneity

decline in absolute values as λ decreases and value concentration increases. The values range from 169 for agent 1 at $\lambda = 1.0$ (maximum equity weighting) to 23 for agent 10 at $\lambda = 0.2$ (maximum efficiency focus), indicating strong differentiation in marginal contributions. These patterns show that moderate changes in λ can generate substantial redistributive effects without reducing efficiency. The right panel displays weekly utilization heterogeneity over the full 52-week cycle. Several agents maintain consistently high utilization (dark green cells), indicating stable baseline demand. Others exhibit highly volatile profiles, with red–orange patches indicating utilization below 65%. This heterogeneity demonstrates the limits of aggregate policy and highlights the need for adaptive resource-allocation mechanisms that respond to both temporal variation and agent-level differences. Effective policy design must therefore rely on decentralized feedback loops capable of detecting and adjusting to these heterogeneous patterns in real time.

11 Limitations and further developments

The proposed model, while offering promising results consistent with the theoretical premises, presents some limitations that are worth discussing and open to interesting prospects for future development.

A first limitation concerns the maximum size of the coalitions considered, set at six agents. This threshold was inspired by the literature on in-person groups, which consensus holds that the optimal size is around 5–7 people (Hackman & Vidmar, 1970; Lakey & Cohen, 2000; Mueller, 2012). While this value has the advantage of limiting computational complexity, it may exclude larger configurations that are potentially more efficient or meaningful for collaboration.

Methodologically, the model uses an approximation in calculating Shapley Values, which is necessary to ensure the tractability of the problem at the network scale. However, this choice introduces uncertainty into the estimation of agents' marginal contributions.

It should also be noted that the model assumes a static structure of agents' preferences and characteristics. In reality, factors such as skills, resource availability, and propensities for collaboration are dynamic and evolve over time.

11.1 Dynamic extensions and future research directions

While the current model assumes static agent characteristics, several promising extensions can incorporate temporal dynamics to enhance both realism and analytical depth. First, the framework can be reformulated as a multi-period model in which coalition values evolve according to learning effects generated by repeated interactions among agents:

$$V_t(S) = V_{t-1}(S) + \gamma \cdot L_t(S) \tag{32}$$

where $L_t(S)$ represents the learning component and $\gamma \in [0, 1]$ denotes the learning rate. This formulation captures the cumulative and adaptive nature of collaborative behavior. Dynamic population mechanisms can also be introduced by allowing agents to enter or exit the system over time. Entry and exit probabilities may be expressed as:

$$P_{entry}(t) = \mu \cdot (1 - N_t/N_{max}) \tag{33}$$

$$P_{exit}(t) = \nu \cdot (1 - V_i(t)/\bar{V}) \tag{34}$$

where μ and ν correspond to the entry and exit rates, N_{max} represents the network's maximum capacity, and $\bar{V}$ is the average value threshold. This approach enables modeling of dynamic ecosystems where participation fluctuates in response to value creation and opportunity structures.

Temporal coalition stability can be further ensured by introducing persistence and reputation mechanisms. Coalitions may be required to remain active for at least τ_{min} periods, while agents incur a switching cost c_{switch} when changing coalitions. In addition, reputation effects can be incorporated to account for how historical performance influences future coalition opportunities. Together, these mechanisms capture the temporal interdependencies that shape cooperative dynamics.

Preliminary simulations over a three-month horizon indicate that the inclusion of these temporal features increases model realism without compromising computational tractability for networks of up to 150 agents. In light of these considerations, future research should explore how varying public policy objectives influence the optimal evolution of the λ parameter over time. It should also assess the long-term territorial impacts of alternative weighting strategies and empirically validate the proposed framework by applying it to real-world co-working networks.

12 Conclusions

Our research confirms and extends the theoretical framework for multi-objective optimization of co-working networks as instruments of public policy for territorial development. The results demonstrate that the dynamic λ adjustment mechanism, based on agents' Shapley Values and guided by public policy objectives, achieves significantly better outcomes than traditional static weighting approaches.

By treating co-working networks as instruments of public policy rather than purely private economic entities, we provide a framework that balances economic efficiency with territorial sustainability and social objectives. The model effectively balances the maximization of collaborative value with the minimization of operational costs.

The bi-objective approach, justified by the need to account for territorial externalities and public policy flexibility, offers decision-makers a transparent and adaptable tool for territorial development.

The model explicitly addresses coalition formation processes, management structures, and resource constraints, providing a comprehensive framework for understanding and optimizing co-working networks as public policy instruments. This approach not only increases the utilization of existing infrastructure but also creates additional value through strategic coalition formation guided by territorial development objectives.

Our application to the Aosta Valley demonstrates the framework's practical applicability and its ability to generate actionable insights for territorial development strategies. The approach represents a significant step toward evidence-based public policy for innovation ecosystem development in both urban and rural contexts. It is particularly relevant for regions facing depopulation, seasonal economic fluctuations, and the need for sustainable territorial development.

Overall, this work provides practical evidence of the effectiveness of the proposed bi-objective optimization framework as a decision-support tool. It can be used by policy makers, co-working space operators, and regional development planners seeking to optimize co-working networks while ensuring alignment with broader territorial development and sustainability objectives.

Acknowledgements Funded by the European Union - NextGenerationEU, Mission 4 Component 2 - ECS00000036 - CUP [B63B22000010001].

Declarations

Conflicts of Interest The authors declare that they have no conflicts of interest.

References

Agrawal, A., Galasso, A., & Oettl, A. (2017). Roads and innovation. *Review of Economics and Statistics, 99*(3), 417–434. https://doi.org/10.1162/REST_a_00619

Alderighi, M., Baroglio, C., Chiesa, M., Ciano, T., Feder, C., Figini, V., Marengo, E. & Tedeschi, S. (2024). Towards a network of co-working spaces for social innovation in mountain areas. In: *Proceedings of the 32nd international conference on enabling technologies: infrastructure for collaborative enterprises*. WETICE, pp. 164–169. IEEE, Los Alamitos, CA, USA (2024). https://doi.org/10.1109/WETICE64632.2024.00017.

Arbolino, R., Boffardi, R., De Simone, L., & Ioppolo, G. (2021). Multi-objective optimization technique: A novel approach in tourism sustainability planning. *Journal of Environmental Management, 285*, Article 112016. https://doi.org/10.1016/j.jenvman.2021.112016

Boudreau, K. J., Brady, T., Ganguli, I., Gaule, P., Guinan, E., Hollenberg, A., & Lakhani, K. R. (2017). A field experiment on search costs and the formation of scientific collaborations. *Review of Economics and Statistics, 99*(4), 565–576. https://doi.org/10.1162/REST_a_00676

Bouncken, R. B., Ratzmann, M., Barwinski, R., & Kraus, S. (2020). Coworking spaces: Empowerment for entrepreneurship and innovation in the digital and sharing economy. *Journal of Business Research, 114*, 102–110. https://doi.org/10.1016/j.jbusres.2020.03.033

Caramia, M., & Dell'Olmo, P. (2020). Multi-objective Management in Freight Logistics: Increasing Capacity, Service Level, Sustainability, and Safety with Optimization Algorithms. Springer, Cham, Switzerland. https://doi.org/10.1007/978-3-030-50812-8

Castro, J., Gómez, D., & Tejada, J. (2009). Polynomial calculation of the shapley value based on sampling. *Computers & Operations Research, 36*(5), 1726–1730. https://doi.org/10.1016/j.cor.2008.04.004

Chan, T. Y., Li, J., & Pierce, L. (2014). Compensation and peer effects in competing sales teams. *Management Science, 60*(8), 1965–1984. https://doi.org/10.1287/mnsc.2013.1840

Chesbrough, H. W. (2003). *Open Innovation: The New Imperative for Creating and Profiting from Technology*. Boston, MA: Harvard Business Press.

Ciano T., Ferrara M. (2024). Shapley value in machine learning modeling: Optimizing decision-making in coworking spaces. *Applied Mathematical Sciences*, *18*(9), 413–429. https://doi.org/10.12988/ams.2024.919155

Deb, K., Sindhya, K., & Hakanen, J. (2016). Multi-objective optimization. In: *Decision sciences: theory and practice*, pp. 161–200. CRC Press, Boca Raton, FL. https://doi.org/10.1201/9781315183176-12

Durante, G., & Turvani, M. (2018). Coworking, the sharing economy, and the city: Which role for the 'coworking entrepreneur'? *Urban Science, 2*(3), 83. https://doi.org/10.3390/urbansci2030083

Fatima, S. S., Wooldridge, M., & Jennings, N. R. (2008). A linear approximation method for the shapley value. *Artificial Intelligence, 172*(14), 1673–1699. https://doi.org/10.1016/j.artint.2008.05.003

Feld, S. L. (1981). The focused organization of social ties. *American Journal of Sociology, 86*(5), 1015–1035. https://doi.org/10.1086/227352

Garrett, L. E., Spreitzer, G. M., & Bacevice, P. A. (2017). Co-constructing a sense of community at work: The emergence of community in coworking spaces. *Organization Studies, 38*(6), 821–842. https://doi.org/10.1177/0170840616685354

Giagkiozis, I., & Fleming, P. J. (2015). Methods for multi-objective optimization: An analysis. *Information Sciences, 293*, 338–350. https://doi.org/10.1016/j.ins.2014.08.071

Gunantara, N. (2018). A review of multi-objective optimization: Methods and its applications. *Cogent Engineering, 5*(1), 1502242. https://doi.org/10.1080/23311916.2018.1502242

Hackman, J.R., & Vidmar, N. (1970). Effects of size and task type on group performance and member reactions. Sociometry, 37–54.

Hasan, S., & Koning, R. (2019). Prior ties and the limits of peer effects on startup team performance. *Strategic Management Journal, 40*(9), 1394–1416. https://doi.org/10.1002/smj.3032

Howell, T. (2022). Coworking spaces: An overview and research agenda. *Research Policy, 51*(2), Article 104447. https://doi.org/10.1016/j.respol.2021.104447

Kahan, J. P., & Rapoport, A. (2014). *Theories of Coalition Formation*. New York, NY: Psychology Press.

Kyriazi, Z., Lejano, R. P., Maes, F., & Degraer, S. (2017). A cooperative game-theoretic framework for negotiating marine spatial allocation agreements among heterogeneous players. *Journal of Environmental Management, 187*, 444–455. https://doi.org/10.1016/j.jenvman.2016.11.011

Lakey, B., & Cohen, S. (2000). Social support theory and measurement. In: *Social support measurement and intervention: a guide for health and social scientists*. Oxford University Press. https://doi.org/10.1093/med:psych/9780195126709.003.0002

Lima, H. C. R. D., Filho, R. A. D. M., Oliveira, B. R. B. D., Lima, T. L. D. A., & Sobral, M. F. F. (2024). Network and business performance installed in coworking spaces: Evidence and associations. *Administrative Sciences, 14*(11), 290. https://doi.org/10.3390/admsci14110290

Lucidi, S., Maurici, M., Paulon, L., Rinaldi, F., & Roma, M. (2016). A simulation-based multiobjective optimization approach for health care service management. *IEEE Transactions on Automation Science and Engineering, 13*(4), 1480–1494. https://doi.org/10.1109/TASE.2016.2574950

Mahdiraji, H. A., Razghandi, E., & Hatami-Marbini, A. (2021). Overlapping coalition formation in game theory: A state-of-the-art review. *Expert Systems with Applications, 174*, Article 114752. https://doi.org/10.1016/j.eswa.2021.114752

Malecki, E. J. (2010). Everywhere? the geography of knowledge. *Journal of Regional Science, 50*(1), 493–513. https://doi.org/10.1111/j.1467-9787.2009.00640.x

Malecki, E. J. (2011). Connecting local entrepreneurial ecosystems to global innovation networks: Open innovation, double networks and knowledge integration. *International Journal of Entrepreneurship and Innovation Management, 14*(1), 36–59. https://doi.org/10.1504/IJEIM.2011.040821

Marden, J. R., & Roughgarden, T. (2014). Generalized efficiency bounds in distributed resource allocation. *IEEE Transactions on Automatic Control, 59*(3), 571–584. https://doi.org/10.1109/TAC.2014.2301613

Marler, R. T., & Arora, J. S. (2010). The weighted sum method for multi-objective optimization: new insights. *Structural and Multidisciplinary Optimization, 41*(6), 853–862. https://doi.org/10.1007/s00158-009-0460-7

Marquis, C. (2003). The pressure of the past: Network imprinting in intercorporate communities. *Administrative Science Quarterly, 48*(4), 655–689. https://doi.org/10.2307/3556640

Moriset, B. (2013). Building new places of the creative economy: The rise of coworking spaces. HAL Archives. hal-00914075.

Mueller, J. S. (2012). Why individuals in larger teams perform worse. *Organizational behavior and human decision processes, 117*(1), 111–124.

Oldenburg, R. (1997). Our vanishing third places. *Planning Commissioners Journal, 25*, 6–10.

Ray, D., & Vohra, R. (2015). Coalition formation. *Handbook of Game Theory with Economic Applications, 4*, 239–326. https://doi.org/10.1016/B978-0-444-53766-9.00005-7

Rosenkopf, L., Metiu, A., & George, V. P. (2001). From the bottom up? technical committee activity and alliance formation. *Administrative Science Quarterly, 46*(4), 748–772. https://doi.org/10.2307/3094830

Rus, A., & Orel, M. (2015). Coworking: A community of work. *Teorija in Praksa, 52*(6), 1017–1038.

Spinuzzi, C. (2012). Working alone together: Coworking as emergent collaborative activity. *Journal of Business and Technical Communication, 26*(4), 399–441. https://doi.org/10.1177/1050651912444070

Stam, W. (2010). Industry event participation and network brokerage among entrepreneurial ventures. *Journal of Management Studies, 47*(4), 625–653. https://doi.org/10.1111/j.1467-6486.2009.00899.x

Wang, W., Liang, J., & Niu, J. (2022). Site selection of co-working spaces under the influence of multiple factors: a case study in hangzhou, china. *Sustainability, 14*(5), 2676. https://doi.org/10.3390/su14052676

Weijs-Perrée, M., Van De Koevering, J., Appel-Meulenbroek, R., & Arentze, T. (2019). Analysing user preferences for co-working space characteristics. *Building Research & Information, 47*(5), 534–548. https://doi.org/10.1080/09613218.2018.1463750

Zafari, F., Li, J., Leung, K.K., Towsley, D., & Swami, A. (2018). A game-theoretic approach to multi-objective resource sharing and allocation in mobile edge clouds. In: Proceedings of the 2018 on Technologies for the Wireless Edge Workshop. WirelessEdge '18, pp. 9–13. ACM, New York, NY. https://doi.org/10.1145/3266276.3266277

Authors and Affiliations

Marco Alderighi[1] · Cristina Baroglio[2] · Mario Chiesa[3] · Tiziana Ciano[4] · Christophe Feder[4] · Valeria Figini[3] · Elisa Marengo[2] · Stefano Tedeschi[4]

✉ Tiziana Ciano
t.ciano@univda.it

Marco Alderighi
marco.alderighi@unimi.it

Cristina Baroglio
cristina.baroglio@unito.it

Mario Chiesa
mario.chiesa@linksfoundation.com

Christophe Feder
c.feder@univda.it

Valeria Figini
valeria.figini@linksfoundation.com

Elisa Marengo
elisa.marengo@unito.it

Stefano Tedeschi
s.tedeschi@univda.it

[1] Università degli Studi di Milano, Department of Economics, Management and Quantitative Methods, Milano, Italy

[2] Computer Science Department, Università degli Studi di Torino, Torino, Italy

[3] LINKS Foundation, Torino, Italy

[4] Department of Economic and Political Sciences, Università della Valle d'Aosta - Université de la Vallée d'Aoste, Aosta, Italy