A comparative analysis of open and closed strategy-making: A simulation study

Ali Banihashemi, Stephan Leitner, Alexandra Rausch, and Gernot Mödritscher

University of Klagenfurt, 9020 Klagenfurt, Austria
{ali.banihashemi, stephan.leitner, alexandra.rausch, gernot.moedritscher}@aau.at

Abstract. Open Strategy is a novel strategy-making approach that considers the inclusion of stakeholders as one of its main principles. While it has the potential to enhance the strategy-making process, there also is a lack of studies examining its long-term effectiveness. To address this gap, we conduct a simulation study to explore the impact of stakeholders' participation in the idea-generation phase on the performance of strategies, considering the complexity of the strategic task, the number of participants, and their objectives' alignment with the organization's objectives. We find that Open Strategy initially outperforms closed strategy-making, but not in the long-term, particularly if the objectives of the participants differ from those of the organization. Additionally, Open Strategy leads to better performance when more participants are involved, and complexity is lower. Our study challenges the prevailing views about Open Strategy as a superior approach to the strategy-making process.

Keywords: Open Strategy, NKCS framework, Agent-based modeling

1 Introduction

Open Strategy is a novel strategy-making approach that considers inclusion as one of its main principles. Inclusion encompasses the involvement of traditionally marginalized stakeholders, such as customers, employees, and suppliers [15]. The specifics of inclusion lead to different practices of Open Strategy and potentially different outcomes. Despite the diversity in practice, every strategy-making process can be considered a three-step process comprising idea generation, strategy selection, and implementation [4]. Although openness can occur throughout all phases, this study focuses on the first phase, as openness appears to be more common during this stage [5].

While Open Strategy is known to have many benefits, it can cause particular challenges and risks. On the bright side, Open Strategy enhances access to information, fosters innovation, and potentially leads to better strategies [6, 10]. However, it also entails risks, such as the opposition of perspectives and interests, the elevation of participants' expectations, frustration, and loss of participants' engagement [6, 10].

The pros and cons of Open Strategy may depend on the characteristics of the stakeholders involved. Stakeholders' objectives play a crucial role in shaping their behavior, making it essential to take them into account [2]. The non-alignment of stakeholders' objectives with the organization's objectives can be a potential source of strategic disagreement. In this regard, research has identified stakeholders' engagement in egotistic behaviors like self-promotion during Open Strategy practices [9] possibly originated from their objectives. In addition, stakeholders' experiences during the process, such as their achievements from established strategies, can also affect their behavior. Satisfying outcomes can enhance stakeholders' motivation and commitment, which are vital for effective inclusion. In return, unsatisfying experiences can create a psychological burden for them, decreasing their motivation and commitment, which can be deleterious for openness [6].

Given that Open Strategy has mainly been practiced as one-time trials [3], it is crucial to investigate its effectiveness in the long run, taking into account stakeholders' behavior and varying contexts. We use an Agent-based model to investigate the impact of the strategic task's complexity [8], the number of participants [4], and the alignment of their objectives with the organization's objectives [9] on the performance of the strategy. The research questions are:

1. How does the performance of resulted strategies differ between open and closed approaches to strategy-making over time?
2. How do the behaviors and number of stakeholders impact the performance of strategies in Open Strategy?
3. How does task complexity affect strategy performance in Open Strategy?

2 Model description

We present a model for open strategy making, consisting of a triadic model involving three distinct types of agents: ***(i)*** the organization, ***(ii)*** stakeholders, and ***(iii)*** the environment.[1] The organization's primary responsibility is to develop a strategic plan, which may occur either through a closed approach (i.e., solely within the organization) or an open approach (i.e., involving stakeholders in the process). Under the latter scenario, stakeholders can submit strategy proposals to the organization. Stakeholders exhibit adaptive behavior, adjusting their participation in strategy sessions based on the outcomes. An overview of the sequence of events during the simulations is provided in Fig. 1.

The organization operates on its landscape and stakeholders operate on correlated versions of the organization's landscape, whereby the value of the correlation coefficient reflects the degree to which stakeholders' objectives are aligned with those of the organization. The environment agent is responsible for capturing external factors that may influence the strategy-making process, such as market forces or competitive pressures. To account for these influences, the utility that the organization and stakeholders draw from strategies is affected by the environment agent. Details are provided in Secs. 2.1 to 2.3.

[1] The implementation of the simulation model was done with Python 3.7.4.

To operationalize our proposed model, we utilize the established $NKCS$ framework [13, 14]. This framework entails using N-dimensional decision problems, within which all agents operate on corresponding landscapes that exhibit K interdependencies. Specifically, the organization and stakeholders are coupled with a single landscape, the environment ($S = 1$). Finally, we can control the strength of the environment's effect on the organization and stakeholders' decision-making process through the parameter C.

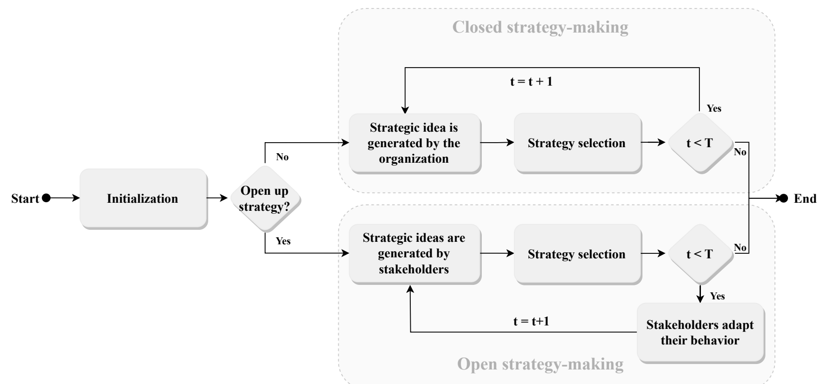

Fig. 1: Sequence of events

2.1 Initialization

Landscapes and performance Our model considers three types of agents: one organization, $l \in \mathbb{N}$ stakeholders, and one environment. The organization and stakeholders aim to maximize the performance of strategies, from which they experience utility, whereas the environment agent acts randomly. The organization's landscape comprises all possible 2^N strategies and the corresponding performance, from which utility can be derived. Each stakeholder operates on its landscape, which is correlated with the organization's landscape and contains the utility that the stakeholder can draw from the 2^N possible strategies. The model accounts for external factors, including the impact of the organizational environment on strategy performance. Further details on how we compute stakeholders' landscapes can be found in Sec. Correlation between landscapes.

We use the notation $\mathbf{B} = \{b_{j=1}, \ldots, b_{j=8}\}$ to represent a specific strategy developed by the organization, and $\mathbf{E} = \{e_{z=1}, \ldots, e_{z=8}\}$ to denote the state of the environment, where $b_j, e_z \in \{0, 1\}$.[2] To account for the complexity arising from these inputs, we employ a contribution function for each bit from the strategy task that reflects the interdependencies between tasks, both internally (within the organization) and externally (from the environment). Specifically, the contribution function incorporates the influence of $K \in \mathbb{N}_0$ other elements of the strategy and $C \in \mathbb{N}_0$ elements of the environment, and, given a state of

[2] Time indices have been omitted in this section for clarity.

the environment E, takes the form

$$^{\text{agent}}(b_j|E) = {}^{\text{agent}}\left(b_j\,;\ \underbrace{b_{j_1},\ldots,b_{j_K}}_{K\ \text{internal elements}}\,;\ \underbrace{e_{z_1},\ldots,e_{z_C}}_{C\ \text{external elements}}\right); \qquad (1)$$

where $^{\text{agent}}(b_j|E) \quad (0,1) \quad \mathbb{R}$ and the superscript "agent" is a placeholder that denotes whether the performance is computed on either the organization's (indicated by superscript "org") or one of the I stakeholders' landscapes (indicated by superscript $i, \ldots, I$). The overall performance of a strategy, given a specific state of the environment E, is computed as the mean of all performance contributions, such that

$$^{\text{agent}}(B|E) = \frac{1}{8}\sum_{b_j \in B} {}^{\text{agent}}(b_j|E) \,. \qquad (2)$$

The environment agent The environment agent's movements on its landscape serve as a measure of environmental changes. These movements reflect the actions of various actors, including competitors, customers, suppliers, governments, and banks. Due to the sheer number of actors involved, we model this agent's movements as random. Specifically, at each time step, the agent randomly moves within a Hamming distance of one or two from its current position with probability P^{env}. This probability reflects the rate of environmental changes, with a higher value indicating a more dynamic environment.[3]

Correlation between landscapes The landscapes of stakeholders and the organization are correlated and coupled to the environmental landscape (Fig. 2). We control the correlation between the organization's landscape and stakeholders' landscapes to represent their alignment. Positive correlation reflects close alignment, while negative correlation indicates a lack of alignment.

To incorporate landscape correlation, we draw correlation values from a skewed distribution $_i \quad (\ 1,1)_{(s)} \quad \mathbb{R}$, where s represents the skewness. This allows us to model scenarios with different stakeholder populations. For example, for a company in the meat substitute industry, negative and positive correlation values represent environmentally conscious stakeholders(aligned) and advocates of the traditional meat industry(not aligned), respectively. The skewness captures the overall alignment of all stakeholders.

We utilize the methodology introduced by [12] to generate correlated landscapes. This method ensures correlated fitness values in multi-objective NK landscapes, constructing landscapes with matching epistasis structures. We create a collection of correlated vectors $(Z_1, Z_2, \ldots, Z_n)$ using a multi-normal distribution with mean border $= \{0, 0, \ldots, 0\}$ and calculate the correlation matrix based

3 While the random movements of the environment agent may affect the utility of strategies for the organization and stakeholders, we are not measuring the environmental agent's utility directly.

on the correlation matrix CM using Eq. 3. The CM matrix describes correlations between landscapes. Correlated landscapes are then obtained by applying the univariate normal cumulative density function, $U(Z_i)$, according to the CM matrix.

$$= 2 \quad \sin(\frac{\ }{6} \quad CM) \tag{3}$$

Fig. 2: Model architecture

2.2 Idea-generation and strategy selection

In this paper, we examine two scenarios for strategy development. Firstly, the traditional approach involves closed strategy development within the organization itself. Secondly, an alternative approach involves opening up the idea-generation phase to stakeholders, allowing their contributions to the strategy-making

Closed strategy making When using a closed approach to strategy making, only the organization is involved in the strategy development process. In an evolutionary sense, the organization randomly develops and evaluates strategies that are similar to the current strategy. More speci cally, the organization randomly discovers a strategy from the neighborhood of the current strategy, with the neighborhood de ned by a Hamming distance of one or two. We denote the developed (or discovered) strategy in period t as $\tilde{B}_t$, and the currently implemented strategy, decided upon on the previous period, as $B_{t\ 1}$. To evaluate the developed strategy, the organization employs a noisy hill-climbing algorithm. The developed strategy is adopted, if it o ers better performance than the currently implemented strategy. However, if the developed strategy does not promise better performance, there is still a chance that it may be implemented because the organization makes sub-optimal choices in strategy selection with a probability of P_t^+. This probability decreases over time, such that $P_t^+ = e^x$ where

$x = (1 + t) =$. The parameter provides control over the rate at which this probability decays. Please note that the organization does not know the environment's moves in advance but only has this information after implementation. Therefore, the evaluation of strategies is based on the state of the environment in the previous period. We formalize the organization's decision rule for closed strategy making as follows:

$$B_t = \begin{cases} \tilde{B}_t & \text{if } {}^{org}(\tilde{B}_t|E_{t-1}) > {}^{org}(B_{t-1}|E_{t-1}) \, ; \\ \tilde{B}_t & \text{with prob. } P_t^+ \text{ if } {}^{org}(\tilde{B}_t|E_{t-1}) \quad {}^{org}(B_{t-1}|E_{t-1}) \, ; \\ B_{t-1} & \text{with prob. } (1 - P_t^+) \text{ if } {}^{org}(\tilde{B}_t|E_{t-1}) \quad {}^{org}(B_{t-1}|E_{t-1}) \, : \end{cases} \tag{4}$$

Open strategy-making In the case of openness, organizations involve stakeholders only in the *idea generation* phase of the process in our model. Specifically, every stakeholder i generates and privately evaluates f_t^i strategies in period t, which are similar to the previously implemented strategy, B_{t-1}, that was chosen and implemented in the prior period. The newly developed strategies are located within the neighborhood of the currently implemented strategy, with the neighborhood defined by a Hamming distance of one or two. Here, f_t^i serves as a proxy for the effort put forth by stakeholder i in the open strategy process during period t. To evaluate these strategies, stakeholders refer to their personal landscapes and select the single strategy that promises the highest performance. This strategy is then forwarded to the organization.

We denote the vector of the currently implemented strategy B_{t-1} and the f_t^i number of strategies developed by stakeholder i in period t by $\tilde{\mathbf{B}}_t^i$. Then, stakeholder i's rule to select a strategy to be forwarded to the organization is:

$$\tilde{B}_t^i = \arg\max_{B' \in \tilde{\mathbf{B}}_t^i} {}^i(B'|E_{t-1}) \quad : \tag{5}$$

Once the included stakeholders forward their proposals, the organization evaluates them and decides which strategy to implement. We can denote the proposals received by the organization as $\tilde{\mathbf{B}}_t^{org}$. The organization identifies the strategy that promises the highest performance according to:

$$\tilde{B}_t^{org} = \arg\max_{B' \in \tilde{\mathbf{B}}_t^{org}} ({}^{org}(B'|E_{t-1})) \quad : \tag{6}$$

Finally, taking the outcome of the strategy development phase into account, the organization decides whether to implement $\tilde{B}_t^{org}$ or stick to the currently implemented strategy B_{t-1} according to the rule introduced in Eq. 4.

2.3 Strategy implementation and stakeholders' adaption

Once the organization has decided on a strategy to be implemented in period t, it moves to this position in the landscape. After implementation, the organization and all stakeholders experience utility from the implemented strategy. In scenarios with open strategy-making, stakeholders develop expectations about the outcome or performance of the strategy-making process when involved. After the strategy implementation, they compare their experienced utility with their expectations and adapt their behavior along two dimensions. The first dimension involves their willingness to participate in the open strategy-making process and the second dimension involves the effort they put forth when participating.

Stakeholders' effort in open strategy making Recall that stakeholders selected a strategy to be forwarded to the organization following Eq. 5, and the corresponding expectation about the performance stakeholder i can draw from the process is $^i(\tilde{B}^i_t|E_{t-1})$. The organization decided to implement strategy B_t following Eqs. 6 and 4, and, as described in Sec. The environment agent, the environment changes with probability P^{env}. Then, stakeholder i computes the extent to which their expectations are met according to

$$ {}^i_t = {}^i(B_t|E_t) \quad {}^i(\tilde{B}^i_t|E_t) : \tag{7}$$

Above, we used the term "effort" to describe the number of strategies developed and evaluated by stakeholders during the strategy-making process. The level of effort exerted by stakeholder i in period t is denoted by f^i_t, which is calculated as the rounded value of f^0_t. Based on the extent to which stakeholder i's expectations are met, they adapt their effort for the next strategy-making round using the following equations:

$$ f^0_{t+1} = f^0_t + {}^i_t \text{ and } f^i_{t+1} = \lfloor f^0_{t+1} \rceil ; \tag{8}$$

where $\lfloor \rceil$ rounds the argument to the nearest integer. If the stakeholders' expectations are met, they are satisfied with the outcome and tend to make more effort in the strategy-making process. In contrast, if stakeholders are dissatisfied, they gradually decrease their effort. It is worth noting that the upper boundary for adaptation is 36, which, given our model, represents the maximum number of strategies technically located in the neighborhood of a Hamming distance of one and two. If the effort reaches the lower boundary of zero, stakeholders will not participate in the process.

Stakeholders' participation in open strategy-making Once a stakeholder is dissatisfied and, consequently, no longer participates in the open strategy-making process, this stakeholder may change its mind and re-enter the process with the probability P^i_t. Specifically, based on ${}^i_t$, stakeholder i adapts this probability using a quasi Bayesian approach [7]. Stakeholder i keeps track of the number of times their expectations are met or not met up to period t using ${}^i_t$ and ${}^i_t$, respectively, and adjusts their behavior using the following rule:

$$ ({}^i_t ; {}^i_t) = \begin{cases} ({}^i_{t-1} + |erf\ {}^i_t| ; {}^i_{t-1}) & \text{if } i\text{'s expectations are met, } {}^i_t \quad 0 ; \\ ({}^i_{t-1} ; {}^i_{t-1} + |erf\ {}^i_t|) & \text{otherwise .} \end{cases} \tag{9}$$

Here, the operator erf refers to the error function used to scale down the effects of satisfaction and dissatisfaction on the probability. The function $|\cdot|$ returns the absolute value of the argument and the probability of returning to the strategy-making process is

$$P_t^i = E(X) = \frac{\alpha_t^i}{\alpha_t^i + \beta_t^i} \quad \text{where } X \sim B(\alpha_t^i, \beta_t^i)\,.[4] \tag{10}$$

3 Simulation experiments

In our analysis, we particularly focus on the following parameters:

Strategy-making mode We investigate the impact on organizational performance when using the closed or open approach to strategy development as described in Section 2.2. The strategy-making mode is controlled by the "mode" parameter, which can take on values of either closed or open.

Number of stakeholders To investigate the relationship between the number of involved stakeholders and the performance of the resulted strategies in open strategy-making modes, we systematically vary the number of stakeholders using the parameter I, which can take on values of either 10 or 20.

The extent to which the stakeholders' objectives overall align with the organization's objectives (Skewness) We control for this characteristic by manipulating the skewness (s) of the distribution from which we draw the stakeholder-specific correlation between their landscape and the organization's landscape. We consider two scenarios in which the majority of stakeholders are characterized by landscapes that are positively or negatively correlated with the organization's landscape. Specifically, we set the skewness parameter to -10 and 10, respectively.

Task complexity To examine the impact of strategic task complexity, we manipulate the interdependencies that shape the performance landscapes using the contribution function introduced in Eq. 1. We consider two cases, i.e., low and high task complexity, as illustrated in Fig. 3. We control for task complexity using the parameter $K \in \{1, 5\}$.

An overview of the main model parameters is provided in Tab. 1. For every scenario, we perform $R = 1{,}000$ simulation runs for $T = 200$ time steps. In the initial step of the simulation, both the environment and the organization are randomly placed in their respective landscapes. While all stakeholders follow the organization's movements, they experience utility based on their own unique landscapes. During the simulations, we monitor the strategies implemented by the organization based on the decision rule introduced in Eq. 4. We use the superscript r to indicate simulation runs and keep track of the organizational

Fig. 3: Interdependence with varying levels of complexity

performance in each period t and simulation run r given the implemented strategies and the states of the environment: $^{org}(B_t^r|E_t^r)$. To ensure comparability across different simulation runs, we normalize the performance by the maximum achievable performance in that simulation run, which we denote as $^{org,r}_{max}$. The normalized performance in period t and simulation run r is calculated as:

$$^{org,r}_{norm} = \frac{^{org}(B_t^r|E_t^r)}{^{org,r}_{max}} \tag{11}$$

Finally, in Sec. 4, we report the average normalized performance:

$$^{org} = \frac{1}{R}\sum_{r=1}^{R} {}^{org,r}_{norm} \tag{12}$$

Table 1: Parameters

Type	Variables	Notation	Values
Independent variables	Strategy-making mode	$mode$	$\{closed, open\}$
	Number of stakeholders	I	$\{10, 20\}$
	Skewness	s	$\{ 10, 10\}$
	Task complexity	K	$\{1, 5\}$
Dependent variable	Average normalized performance	^{org}	$(0, 1)$
Other parameters	Landscape parameter	(N, C, S)	$(8, 1, 1)$
	Simulation runs	R	$1,000$
	Timesteps per simulation run	T	200
	Probability of change for environment agent	P^{env}	0.2
	Decay parameter for the organization's decision rule		9
	Initial value for stakeholder i's effort	$f^i_{t=0}$	1
	Initial values for stakeholder i's satisfaction/dissatisfaction	$(^i_{t=0}, ^i_{t=0})$	$(0.5, 0.5)$

The study aims to investigate the impact of an open-strategy approach in the idea-generation phase of strategy-making on performance as compared to a closed-strategy approach. Figure 4 shows the first results for both approaches with (i) 10 or 20 stakeholders and (ii) low and high complexity of the strategic task.

4 Results and discussion

Openness over time Overall, an open-strategy approach yields higher performance than a closed-strategy approach if stakeholders' objectives align with the organization's objectives. The performance difference diminishes in the long run. If stakeholders' objectives do not align with the organization's objectives, the benefits of an open approach vary and may vanish over time, depending on the number of stakeholders involved and the complexity level. For correlated objectives, an open approach is more beneficial in the early stages, as it initially increases performance to a higher level than a closed approach. However, after reaching the peak, performance gradually decreases for an open approach, while a closed approach shows a steady increase.

Hautz [6] offers explanations for these results. In the long run, raised expectations, frustration due to strategic task pressure, and loss of commitment can adversely affect the strategy-making process. Fulfilling stakeholders' expectations becomes challenging, especially when their interests are incompatible with the organization's. Negative experiences may lead stakeholders to reduce their effort in future open strategy sessions. This continuous negative experience can result in higher dissatisfaction, increased inclination to quit the process, and a decrease in information diversity in subsequent strategy-making phases.

Number of stakeholders involved Our results demonstrate that involving a greater number of stakeholders during the idea-generation phase significantly improves the performance of the strategy-making process. This finding aligns with Hautz's [4] insights and Stieger et al.'s [11] research, emphasizing the benefits of a larger network of participants. The positive effect is particularly observed in the early stages and for both complexity levels when stakeholders' objectives are not aligned with the organization's. More stakeholders compensate for the lack of alignment, providing a greater diversity of strategic ideas and alternatives for subsequent strategy-making phases. However, in the long run, and with high complexity, the positive impact diminishes due to stakeholders' negative experiences leading to frustration and disengagement.

Strategic task complexity The benefits of an open approach compared to a closed approach are significantly influenced by the complexity of the strategic task. Overall, performance is lower when complexity is high, and the open strategy approach is more sensitive to changes in complexity. The decrease in performance due to increased complexity is more evident in the open idea-generation phase. Crowdsourcing, as indicated by previous research [1], is better suited for tasks with lower complexity, which is supported by our results in the short run.

Fig. 4: Strategy performances by scenario, 95% confidence level (shaded)

However, in the long run, both open and closed approaches achieve comparable performance levels for low complexity. A closed approach can be as effective as an open approach for highly complex tasks. This finding aligns with previous studies highlighting the importance of considering strategic task difficulty when planning for openness [8, 10].

5 Conclusion

This study explores the impact of openness in the idea-generation phase on strategy performance. Results indicate that while openness has more positive effects in the short term, a closed approach may be more effective in the long term, especially in contexts with complex strategic tasks and a low number of participants with nonaligned objectives. This challenges prevailing views on Open Strategy and emphasizes the need to balance openness with stability and control in strategic decision-making.

This study has limitations worth considering. Firstly, open and closed approaches may have different decision-making speeds, with stakeholder inclusion potentially slowing down the process. Secondly, stakeholders may be influenced by factors beyond strategy utility, such as incentives provided by the organization which can ameliorate the performance. Thirdly, the study assumes a single method of strategy-making throughout an organization's life cycle, whereas, in reality, organizations may switch between different methods based on specific conditions. Finally, the model does not account for the costs associated with increased inclusion and its potential negative impact on performance. While the model demonstrates the benefits of greater inclusion, the cost-benefit ratio should be considered.

References

1. Afuah, A., Tucci, C.L.: Crowdsourcing as a solution to distant search. Academy of Management Review 37(3), 355–375 (2012)
2. Friedman, A.L., Miles, S.: Developing stakeholder theory. Journal of Management Studies 39(1), 1–21 (2002)
3. Hansen, J.R., Pop, M., Skov, M.B., George, B.: A review of open strategy: bridging strategy and public management research. Public Management Review pp. 1–23 (2022)
4. Hautz, J.: Opening up the strategy process–a network perspective. Management Decision 55(9), 1956–1983 (2017)
5. Hautz, J., Hutter, K., Sutter, J., Füller, J.: Practices of inclusion in open strategy. In: Cambridge Handbook of Open Strategy, pp. 87–105. Cambridge University Press (2019)
6. Hautz, J., Seidl, D., Whittington, R.: Open strategy: Dimensions, dilemmas, dynamics. Long Range Planning 50(3), 298–309 (2017)
7. Leitner, S.: Collaborative search and autonomous task allocation in organizations of learning agents. In: Advances in Social Simulation. Springer Nature Switzerland AG (2023), forthcoming.
8. Malhotra, A., Majchrzak, A., Whittington, R., Seidl, D., Von Krogh, G.: Crowdsourcing in open strategy: What can open strategy learn from open innovation. Cambridge Handbook of Open Strategy pp. 121–1135 (2019)
9. Malhotra, A., Majchrzak, A., Niemiec, R.M.: Using public crowds for open strategy formulation: Mitigating the risks of knowledge gaps. Long Range Planning 50(3), 397–410 (2017)
10. Seidl, D., Von Krogh, G., Whittington, R.: Defining open strategy: Dimensions, practices, impacts, and perspectives. Cambridge Handbook of Open Strategy pp. 9–26 (2019)
11. Stieger, D., Matzler, K., Chatterjee, S., Ladstaetter-Fussenegger, F.: Democratizing strategy: How crowdsourcing can be used for strategy dialogues. California Management Review 54(4), 44–68 (2012)
12. Verel, S., Liefooghe, A., Jourdan, L., Dhaenens, C.: On the structure of multi-objective combinatorial search space: MNK-landscapes with correlated objectives. European Journal of Operational Research 227(2), 331–342 (2013)
13. Vidgen, R., Bull, L.: Applications of Kauffman's NKCS model to Management and Organiaztion studies. In: The SAGE Handbook of Complexity and Management, pp. 201–219. Sage (2011)
14. Wall, F., Leitner, S.: Agent-based computational economics in management accounting research: Opportunities and difficulties. Journal of Management Accounting Research 33(3), 189–212 (2021)
15. Whittington, R., Cailluet, L., Yakis-Douglas, B.: Opening strategy: Evolution of a precarious profession. British Journal of Management 22(3), 531–544 (2011)