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ORIGINAL ARTICLE

To be more independent or more dependent? The evolution mechanism of co-innovation between digital platforms and content creators

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ABSTRACT
Co-innovation between digital platforms and complementors is motivated by their interactions, especially on content creation platforms that emphasise creativity. With the platform monopoly, creators are increasingly dependent on the platform thus making the interaction directional. As the long-term effect of the dependency effect on co-innovation under multi-agent networks is currently under-researched, a novel asymmetric NK model is proposed in this paper to evaluate creators' dependence on the platform through agent-based simulation. The results show that the internal interaction of creators has an inverted U-shaped effect on co-innovation, and the external dependency effect has a negative effect on co-innovation. Further results considering global complexity constraints show that there is a substitution effect between internal interaction and external dependency and that relying on a platform can facilitate co-innovation by reducing potential external risks under high environmental complexity. Moreover, exploratory innovation is equally conducive to co-innovation and enables creators to be less dependent. This study extends a new model for digital platform research and responds to discussions between interaction, exploration, and innovation in the literature.

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Digital platforms; co-innovation; dependency effects; agent-based simulation; NK model

1. Introduction

In the digital economy era, digital platforms have integrated and facilitated the creation, promotion, and sale of digital content to attract users for consumption (Wang, Li, & Yi, 2021). With the rapid development of the Mobile Internet and the widespread popularity of smartphones, this business model has given rise to various manifestations, such as mobile app development, live streaming, live e-commerce, mobile videos, and knowledge content creation. Social media literature often refers to creators on digital platforms as content creators (Wei, Wang, & Chang, 2021). It is noteworthy that many consumers who were at the tail end of the supply chain have become content creators through customer entrepreneurship, expanding the supply of content while attracting new consumers, which has led to the rapid development of the business model (Park, Kim, Jeong, & Minshall, 2021). As the industry has matured, leading platforms have monopolised the market, for example, Tik-Tok in mobile video, iOS and Android in mobile app development, Taobao in live e-commerce, and Reddit in knowledge communities. Consequently, many content creators rely on the leading platforms to produce and sell digital content. Moreover, content creation is an extremely innovation-intensive industry that requires constant content innovation to promote new consumption motivations. Therefore, platforms and creators obtain a sustainable competitive advantage through co-innovation (Shree, Kumar Singh, Paul, Hao, & Xu, 2021).

As co-innovators, the interaction between digital platforms and content creators is critical to the mechanism of co-innovation (Abbate, Codini, & Aquilani, 2019). Specifically, digital platforms attract content creators through various methods, such as advertising, publicity, monetary incentives, openness, and a favourable creative environment. Simultaneously, creators leverage the platforms' marketing resources, incentives, and creative communities to undertake innovation (Gawer, 2021). The agility, flexibility, and interactivity of the business model emphasise the importance of interaction, continuous innovation, and co-innovation, which is one of the key elements of value co-creation (Lee, Olson, & Trimi, 2012). The interaction between platforms and creators leads to digital innovation networks, which, in turn, form an ecosystem of co-innovation.

However, the interaction between the creators and platforms is a black box. On the one hand, platforms extract a portion of the creator's earnings, which gives the creator strong motivation to remain

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independent or raise the need for multihoming. On the other hand, platforms also endeavour to provide creators with resources and markets and help them to innovate (Mosterd, Sobota, Kaa, Ding, & Reuver, 2021). Thus, content creators need to rely on the platform's resources to expand their market, but, at the same time, want to be less dependent and thus maintain higher bargaining power (Ghazawneh & Henfridsson, 2013). For example, in practice, the majority of mobile video creators rely on Tik-Tok to post videos and generate revenue, but some creators also post videos on other platforms, such as YouTube and Instagram Reels, even though the advertising extractions for YouTube are much higher than for Tik-Tok (45% vs. 30%). The questions are, therefore, naturally posed: what factors have changed creators' dependence on platforms, and how has creators' dependence on platforms influenced co-innovation?

A novel asymmetric NK model was constructed to illustrate the evolutionary mechanisms of co-innovation based on the theory of adaptive search for complex networks and rugged landscapes (Barabási & Albert, 1999; Levinthal, 1997). The agent-based algorithm was utilised to better understand the difference between internal interaction and external dependency to contribute to operations research (OR) on complex digital networks. According to the findings, creators' dependency on co-innovation is disincentivised for low environmental complexity, but as external complexity increases, the dependency effect exhibits a substitution effect. Especially under high uncertainty, choosing to rely more on digital platforms helps avoid the potential risk of failure. Moreover, the exploration of creators attenuates dependency motivation. The contributions are two-fold. First, a modified NK model is introduced to describe the asymmetric directional effects of the interaction. Second, the constraints and influences of environmental complexity on long-term co-innovation are also considered. Accordingly, this research aims to more closely link the findings regarding (1) the advantages and disadvantages of dependency effects, (2) the substitution effects of decision complexity and dependency effects, and (3) the effects of environmental complexity and exploration on co-innovation to empirical and theoretical studies in related domains.

2. Literature review

2.1. Co-innovation and interaction

Digital platforms and content creators facilitate co-innovation through the interaction of behaviour and decisions, which enhances agile responsiveness to environmental changes and the capacity to create continuous business value (Simon, 1955). Bresciani, Ciampi, Meli, & Ferraris (2021) argued that digital platform-based co-innovation differs from formal collaborative innovation in that co-innovation is coupled in the agents' decision-making process. Each agent located in the network nodes drives cooperation and co-innovation through the interaction of decisions (Lenox, Rockart, & Lewin, 2006). The network structure is formed on the basis of the interface by platforms and the boundaries by creators as the basis for decision-making interactions (Gawer, 2021). Meanwhile, content creators, rather than digital platforms, produce digital content directly, thereby encouraging consumers to create business value (Wei, Wang, & Chang, 2021). Platforms, therefore, also need to promote continuous co-innovation through constant interaction with content creators' innovative activities, which also works to absorb more innovative creators (Mosterd, Sobota, Kaa, Ding, & Reuver, 2021).

It is commonly assumed in the existing literature that decision structure interactions, knowledge interactions, and cross-level interactions in cross-organisational collaborations are undirected. (Hahn & Lee, 2021; Raveendran, Silvestri, & Gulati, 2020). However, driven by capital and network effects, the leading platforms monopolise the market (Evans & Schmalensee, 2017). Therefore, many creators rely on the leading platforms in the market for business activities. This has also had an impact on the network structure, giving the decision network a significant scale-free character (Abbate, Codini, & Aquilani, 2019; Barabási & Albert, 1999). The centrality of digital platforms radiates to every creator, whereas any specific content creator has almost no impact on the platform. Hence, there are directions for interaction in a decision network consisting of digital platforms and content creators, which is referred to as the *dependency effect* from content creators on digital platforms in this paper.

Thus, the digital platform and numerous creators together form a complex network of interactive decisions and co-innovation. The intervention in decision-making spreads from the centre of the platform to the nodes of the creators. Then, collaborative coupling mechanisms are used to achieve co-innovation between platforms and creators (Bresciani, Ciampi, Meli, & Ferraris, 2021). Therefore, co-innovation increases the business value of the digital network and couples the innovation value to be distributed to each node. Accordingly, platforms and creators are strongly motivated to co-innovate and promote co-innovation through various formal or informal methods.

From a platform perspective, platforms need the dependency of external creators, while also being able to leverage the dependency effect to maintain their own competitive advantage. Sedera, Lokuge, Grover, Sarker, & Sarker (2016) argued that digital platforms need to be more scalable; otherwise, it will be difficult to support continuous innovation. Owing to the open nature of digital platforms, the lower limit of the stickiness of external participants is low. It is difficult for platforms to innovate, or even to make profits, after losing the creators who depend on them (Ghazawneh & Henfridsson, 2013). Abbate, Codini, & Aquilani (2019) considered that platforms can rely on intellectual property rights, patents, and other knowledge governance mechanisms to facilitate coupling and value co-creation between platforms and participants. Regardless of the governance mechanism, digital platforms always want to impose some means on content creators to engage participants in value co-creation innovation activities. For content creators, dependence on digital platforms undermines the ability and opportunity to innovate on their own and may also make creators' own innovative behaviour subject to more extraneous factors (Wei, Wang, & Chang, 2021). However, good collaboration and a competitive atmosphere also provide a better platform for creators, as well as helping to hedge against the potential risk of innovation failure (Park, Kim, Jeong, & Minshall, 2021; Shree, Kumar Singh, Paul, Hao, & Xu, 2021).

2.2. Adaptive search and complexity of interaction

The long-term decision-making and innovation process is a topic of extensive interest in OR literature (Bresciani, Ciampi, Meli, & Ferraris, 2021; Ji & Gunasekaran, 2014). Adaptive search aptly describes the long-term innovation process, in which decision makers search and find the optimal decision combination by order with interactive decision attributes in the decision space (Chen, Kaul, & Wu, 2019; Puranam, Stieglitz, Osman, & Pillutla, 2015). The essence of innovation is to break the current situation and improve or explore new production, behaviour, and business modes to obtain excess returns. Decision change leads to innovation and long-term decision-making leads to innovation evolution (Baum, Cowan, & Jonard, 2010). Therefore, it can also be found that innovation is not a short-term behaviour because short-term decision-making changes are almost impossible to significantly promote performance improvement (Guinea & Raymond, 2020). In the long run, however, continuous optimisation of decision-making makes the benefits of innovation iterative and accumulated; that is, there should be a potential space for higher performance as innovators, but must pay for it with time and experience. Several seemingly independent factors can have a significant impact on the value of collaboration between a platform and the complementors in the interaction of long-term decisions (Gawer, 2021).

The interaction of attributes is an abstract microscopic feature of the development of any decision and thus of innovation (Baumann, Schmidt, & Stieglitz, 2019). The interaction of decision attributes is indexed by complexity, with highly complex decision combinations having most of their attributes interacting with each other, whereas the attributes of low-complexity decision combinations are independent of each other (Garcia, 2005). In practice, the complexity of digital platforms and content creators' decisions is macroscopically expressed in the structural complexity of business activities. Examples include the complexity of the platform's organisational, process, and people structures, and the complexity of the creator's content, brand, and consumer structures (Hamer & Frenken, 2021). Furthermore, due to the motivation for co-innovation based on the network structure between the platform and the creator, there is a directed external interaction between the attributes of the platform and the creator's decisions, that is, the dependency effect. The interaction of attributes of the dependency effect is also illustrated by indicators of complexity, such as the pricing structure, promotion structure, and revenue share structure of the platform for creators.

An adaptive search is effective for innovation with massive interaction issues in OR literature (Simon, 1955; Terjesen & Patel, 2017). There are three key points here: the complexity of decisions, search by combination, and search by order. Decision complexity arises from the interactions between attributes. Adaptive search is significantly more difficult as the complexity of the interaction increases, which is called a rugged landscape in the literature (Baumann, Schmidt, & Stieglitz, 2019; Levinthal, 1997). Complexity arises from three aspects: the internal complexity of each platform and creator and the external dependency effect between them. Owing to the non-linearity caused by the interaction between attributes, the optimisation for each single attribute appears meaningless. Therefore, optimisation must be considered in the form of decision combinations, including internal interaction and external dependency (Uotila, Keil, & Maula, 2017). Finally, the rugged landscape, which is based on a combination search, makes the adaptive search process dependent on ordinal search. Decision makers always reach a better decision combination than the current state rather than directly reaching the best decision combination (Levinthal & Workiewicz, 2018; Rahmandad, 2019). In addition,- decision makers can, of course, avoid falling into the trap of local peaks by expanding the search radius (Wu, Lao, Wan, & Li, 2019).

In summary, the dependency effect extends the direction of the interaction effect. The literature explores the interaction between platforms and participants based on adaptive search, but lacks a model to measure the asymmetry of the interaction between platforms and creators (Brunswicker, Almirall, & Majchrzak, 2019; Hamer & Frenken, 2021). Coupling and collaboration in complex networks can improve the overall performance of the system; however, how the dependency effect affects the mechanism based on long-term decision-making interaction remains a black box. This study addressed these issues by improving the NK model and using computational methodologies, potentially contributing new insights to the evolution of innovation (Ji & Gunasekaran, 2014), value co-creation in platforms (Wang, Li, & Yi, 2021), and agent-based computational models (Kapsali, Bayer, Brailsford, & Bolt, 2022) in the field of OR.

3. Model, methodology, and validation

3.1. NK model with asymmetric modification

The NK model is considered an effective method for modelling adaptive search and evolution trends in the interactive decision space (Brunswicker, Almirall, & Majchrzak, 2019), which originated in ecology (Kauffman, 1993). Since its application to management by Levinthal (1997), the NK model has been widely used in management to simulate the evolution of the impact of interacting decision factors on global decision performance in complex systems (Chen, Kaul, & Wu, 2019; Levinthal & Workiewicz, 2018). The basic idea of the NK model suggests that decision-making and innovation are not short-term behaviours, but a long-term process of searching for superiority by different, interacting decision factors in the co-innovation process, which is similar to the real process of innovation in business.

The baseline NK model can be used to describe competitive enterprise decision-making with complementors under distributed search (Baumann, Schmidt, & Stieglitz, 2019). According to these assumptions, there are N binary attributes in the decision space, and normally using 0 and 1 to represent different states of each attribute n_i, so there are 2^N combinations of states in the decision space. K represents the interactivity between these N attributes, and each attribute n_i is affected by other K attributes from n_{i_1} to n_{i_K}. Therefore, the value of K is an integer between 0 and $N-1$, which determines the form of the influence matrix among the N decision dimensions. The decision complexity is lowest when $K=0$, and the influence matrix is a unit matrix of order N, indicating that different decisions are independent of each other. The decision complexity is highest when $K = N-1$, and all values of the influence matrix are 1, indicating that all decisions interact with the others. As K increases, the interaction between attributes also increases, indicating the model has a higher complexity (Levinthal, 1997). Table 1 presents the symbols and representations of the model.

Different portfolios of decisions lead to different performances, and agents optimise their portfolio to achieve better innovation performance. According to the baseline NK model, each performance portfolio $\mathbf{d}$ is a vector of N binary attributes. It is assumed that each attribute has the same weight as these attributes represent the universal decision factors of firms or individuals (Csaszar, 2018). Therefore, the interaction is also considered to be

Table 1. The symbols and representation of the model.

Symbols	Representation in the model
Baseline NK model	
N	The number of the decision components.
n_i	The component i, which can be in either of two states (0 and 1).
K	Each component n_i depends on K other components $n_{i_1}, n_{i_2}, \ldots, n_{i_K}$, represents decision complexity, takes value of $[0, N-1]$.
$\mathbf{d}$	Decision vector $n_1, n_2, \ldots, n_N$.
$f_i(n_{i_1}, n_{i_2}, \ldots, n_{i_K})$	The contribution of component n_i in the fitness value of vector $\mathbf{d}$.
$F(\mathbf{d})$	The fitness value of decision vector $\mathbf{d}$.
The modified asymmetric NK model	
N^p	Parameter, number of the decision attributes of digital platforms.
N^c	Parameter, number of the decision attributes of content creators.
K^p	Parameter, decision complexity of digital platforms, takes the integer in the value of $[0, N^p-1]$.
K^c	Variable, decision complexity of content creators, takes the integer in the value of $[0, N^c-1]$.
L	Variable, the dependency effect from digital platforms links to content creators, takes the integer in the value of $[1, N^p]$.
$\mathbf{d}^p$	Decision vector of digital platforms $\mathbf{d}^p[n_1^p, n_2^p, \ldots, n_{N^p}]$.
$\mathbf{d}^c$	Decision vector of content creators $\mathbf{d}^c[n_1^c, n_2^c, \ldots, n_{N^c}]$.
p	Parameter, the probability of exploratory of content creators, takes value of 0.3, 0.5, and 0.7.
K_{ave}	Indices, represents the average complexity of the overall environment, takes value through Equation 3.
t	Variable, represents the time variable.

homogeneous and random, with the fitness of portfolios being the average of the fitness for each attribute after considering the interaction (Levinthal, 1997). Equation 1 shows the calculation, where $f_i(n_i)$ denotes the initial fitness value of each attribute n_i, but since each attribute n_i is influenced by the other K attributes according to the influence matrix, its interaction fitness value is represented by $f_i(n_i; n_{i_1}, n_{i_2}, \ldots, n_{i_K})$.

$$F(\mathbf{d}) = \frac{1}{N}\sum_{i=1}^{N} f_i(n_i; n_{i_1}, n_{i_2}, \ldots, n_{i_K}) \tag{1}$$

In the baseline NK model, it is assumed that each decision of the agent is a homogeneous decision in the same complex environment, that is, each attribute n_i is affected by other K attributes. However, because of the monopoly of digital platforms, the platforms' decisions have stronger interventions on the creators; therefore, the baseline model has limitations in describing this business decision process. Accordingly, the NK model is modified in two steps to illustrate the strength and direction of the dependency effect. First, the decision attributes are divided into two parts: the platform is $N^p\{n_1^p, n_2^p, \ldots, n_{N^p}^p\}$ and the content creators are $N^c\{n_1^c, n_2^c, \ldots, n_{N^c}^c\}$. Thus, the decision vector $\mathbf{d}[\mathbf{d}^p, \mathbf{d}^c]$ of co-innovation consists of the vectors $\mathbf{d}^p[n_1^p, n_2^p, \ldots, n_{N^p}^p]$ and $\mathbf{d}^c[n_1^c, n_2^c, \ldots, n_{N^c}^c]$, where each $n\{n^p, n^c\}$ takes a value of $\{0, 1\}$.

Second, the influence matrix was modified to present the asymmetrical network relationships and directions of dependency. Interactions are divided into three types: interaction portfolios within digital platforms, interaction portfolios within content creators, and interaction portfolios between digital platforms and content creators, where the interaction between the platforms and creators are directed, which are linked from $\mathbf{d}^p$ to $\mathbf{d}^c$, and, thus, the parameter L was used to represent the directed interaction. L takes the value of an integer between 1 and N^p, meaning that each decision of the creator depends on the average of L decisions of the platform. With these two steps, the modified model can represent two sets of decision agents simultaneously, that is, digital platforms and content creation. It also describes the asymmetric interaction between attributes, in which the attributes of the platform have additional interventions for the attributes of the creators. Therefore, the entire influence matrix was split into four submatrices with complexities K^p, K^c,L, and 0, respectively. According to the assumptions of the baseline model and the modification of the asymmetric model, Equation 2 is utilised to calculate the co-innovation performance.

$$\begin{aligned} F(\mathbf{d}) &= \frac{F(\mathbf{d}^p) + F(\mathbf{d}^c)}{N^p + N^c} \\ \textit{and}: \quad F(\mathbf{d}^p) &= \sum_{i=1}^{N^p} f_i(n_i^p; n_{i_1}^p, n_{i_2}^p, \ldots, n_{i_{K^p}}^p), \\ F(\mathbf{d}^c) &= \sum_{j=1}^{N^c} f_j(n_j^c; n_{j_1}^c, n_{j_2}^c, \ldots, n_{j_{K^c}}^c, n_{j_1}^p, n_{j_2}^p, \ldots, n_{j_L}^p) \end{aligned} \tag{2}$$

As the interaction of decisions is asymmetric, a parameter K_{ave} is constructed by a weighted average of the three types of interactions as a way to represent the global complexity of the landscapes, calculated by Equation 3. According to Equation 3, when the number of attributes and the decision complexity of platforms are controlled, the same K_{ave} can be obtained through different combinations of K^c and L. Thus, even with the same environmental complexity, different combinations of dependency effects and internal interactions for creators still exist. Utilising sets of dependency effects, it is possible to assess the strength of the dependency effects under the same conditions of complexity and more intuitively reflect the mechanisms of the impact on co-innovation.

$$K_{ave} = \frac{K^p N^p + K^c N^c + L N^c}{N^p + N^c} \tag{3}$$

3.2. Agent-based simulation with asymmetric NK model

Agent-based models (ABM) were used for the calculations and simulations. There are two critical advantages of the methodology. The first is that ABM is suitable for exploratory studies of unknown systems, and it enables modelling and simulation of complex systems (Garcia, 2005). For typical mathematical or empirical methods, it is usually difficult to construct complex system models because of the complexity and difficulty in obtaining data. Another benefit is that ABM simulates the real decision-making, behaviour, and innovation of individuals or organisations, which is similar to laboratory experiments (Kapsali, Bayer, Brailsford, & Bolt, 2022).

Innovative agents search for better decision combinations, and every agent intends to seek a better portfolio earlier through their innovative decisions to gain a first-mover advantage and excess returns. Supposed the agent has an initial decision combination $\mathbf{d}_a$, and as time t advances, the agent randomly changes one attribute per unit of time to form a new portfolio, $\mathbf{d}_b$. If the overall performance $F(\mathbf{d}_b)$ is higher than $F(\mathbf{d}_a)$, the decision $\mathbf{d}_a$ is replaced; otherwise, the original portfolio $\mathbf{d}_a$ is retained. As the experiment is repeated millions of times, it is sufficient to characterise the real market, despite the

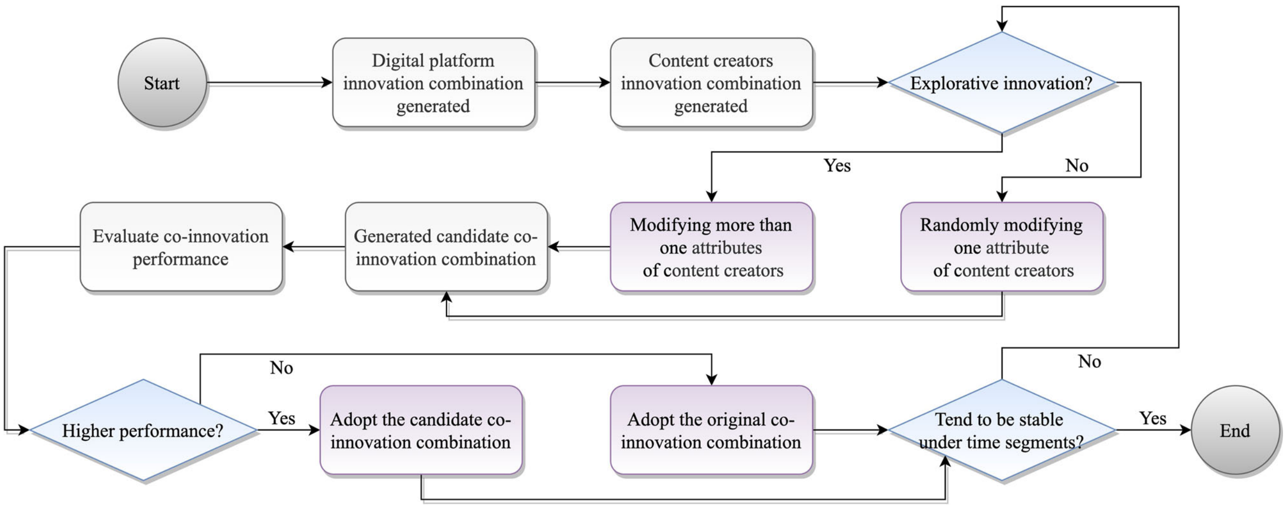

Figure 1. The process of agent-based simulation.

fact that the initial decision combinations were given randomly and the attributes were changed randomly (Baumann, Schmidt, & Stieglitz, 2019). During the evolutionary cycle, agents' co-innovation performance increases and plateaus, reaching a local or global optimum.

To simplify and abstract the model based on the scale-free property of the co-innovation network structure, it is assumed that there is only one digital platform in the market and that a large number of heterogeneous external creators develop their products around the platform. Therefore, decision vector $\mathbf{d}[\mathbf{d}^p, \mathbf{d}^c]$ contains a fixed initial value for each $\mathbf{d}^p$ and a random initial value for each $\mathbf{d}^c$, where the $\mathbf{d}^p$ did not change anymore in the current decision space. Adaptive search algorithms were then used to obtain stable long-term co-innovation performance for content creators.

However, the current literature shows that as the complexity between attributes increases, the number of local peaks grows exponentially (Kauffman, 1993). Agents with only local search can easily fall into the trap of local peaks in a rugged landscape, where no change in any decision factor can increase the overall performance, creating the illusion that innovation is ineffective. Exploration is an effective way of breaking out of the local peak trap, which is a long-distance adaptive search (Lenox, Rockart, & Lewin, 2006; Uotila, Keil, & Maula, 2017; Wu, Lao, Wan, & Li, 2019). Creators combine to achieve growth in innovation performance through conservative exploitation and radical exploration of innovation, which is similar to the concept of exploitative and explorative innovation in the theory of innovation ambidexterity (Guinea & Raymond, 2020; Hamer & Frenken, 2021).

The adaptive search with exploratory algorithm is used to represent the process of co-innovation. Exploitation primarily utilises the existing decision framework by changing one of the decision factors. By changing two or more values of the attributes in the portfolio, the agent can obtain new portfolios to break through the local peak, which means more substantial explorative innovation. However, exploration entails both a higher potential excess return and higher risk for the agents. Therefore, despite the importance of exploratory innovation being emphasised, each creator's preference for exploratory innovation is different because of the higher cost and risk compared to exploitative innovation. For this purpose, probability p is used to denote the probability that a creator may explore rather than exploit it during co-innovation evolution. Based on the modified asymmetric NK model and adaptive search with the exploration algorithm, Figure 1 shows the flow of the simulations and experiments.

Variables and parameters are assigned values to simplify unnecessary algorithmic redundancy and improve experimental efficiency. First, the computational requirement is significantly increased with an increase in N, but the results are not as sensitive to the value of N (Hahn & Lee, 2021; Terjesen & Patel, 2017). This paper mainly shows the simulation results for $N^p = N^c = 7$ and $N = 14$, which is commonly used in the literature (Uotila, Keil, & Maula, 2017). For sensitivity analysis, N is assigned other values and different combinations of N^p and N^c are given to indicate platforms with more intervention, balanced type, and less intervention. The simulation results are shown in Appendix B.

The decision complexity of the platform was assumed to be moderate, that is, $K^p = \frac{N^p-1}{2}$. Then, the evolution mechanisms were explored by taking different ranges, $K^c \in [0, N^c-1]$ and $L \in [1, N^p]$, respectively. Therefore, the range of K_{ave} is calculated using Equation 3. The evolutionary period t is set to 50, as the evolutionary curve of co-innovation performance to be sufficient to eventually level off over this period. Typically, there is no endogenous motivation to change the system until the innovative system has stabilised. The time variable t therefore represents a decision cycle in business practice, which for different businesses may be a month, a quarter or a year. In addition, the actual preferences of the exploration were considered, and the p was adopted as three possible values of 0.3, 0.5, and 0.7, representing the three possible preferences of low, medium, and high explorative innovations, respectively. Based on the above assumptions and parameter settings, to ensure the accuracy of the simulation model, this research simulated approximately 500,000 landscapes and searched more than 7.5 million times. The program was implemented in Python 3.8. For better visualisation of the code structure and to facilitate the repetition of the experimental results, the pseudo-code is shown in Appendix A.

3.3. Model validation

Referring to the methodology of similar studies, the following three efforts were made to ensure the validity of the model (Brunswicker, Almirall, & Majchrzak, 2019; Hahn & Lee, 2021). First, the variables, parameters, relationships, and assumptions of the model must be consistent with reality. To accomplish this, the majority of the variables and parameter settings in this study are informed by existing research, and the assumptions are formulated, giving clear examples from practice. Second, the consistency of the results of the study with empirical research is also discussed in the results section as a way of supporting the validity of the conclusions. Finally, a series of sensitivity analyses were performed to ensure the robustness of the research conclusions.

4. Results and discussion

4.1. Simulation results

Figure 2 shows the experimental results for moderate-level exploration ($p = 0.5$). As the complexity of creators' decisions increases, co-innovation performance always has an inverted U-shape, regardless of how strong the creator-dependent effects are according to the left panel of Figure 2. Co-innovation performance grows rapidly as decision complexity increases from low to moderate levels and is more accentuated on agents with higher dependency effects. When decision complexity continues to grow from moderate to high levels, the fitness value of co-innovation decreases, but at a slightly lower rate than the previous increase.

Regardless of the dependency effect, a medium level of interactive complexity in the creators' internal decision combinations is conducive to achieving better performance. The interaction of decision information enhances the relevance and effectiveness of different types of information,

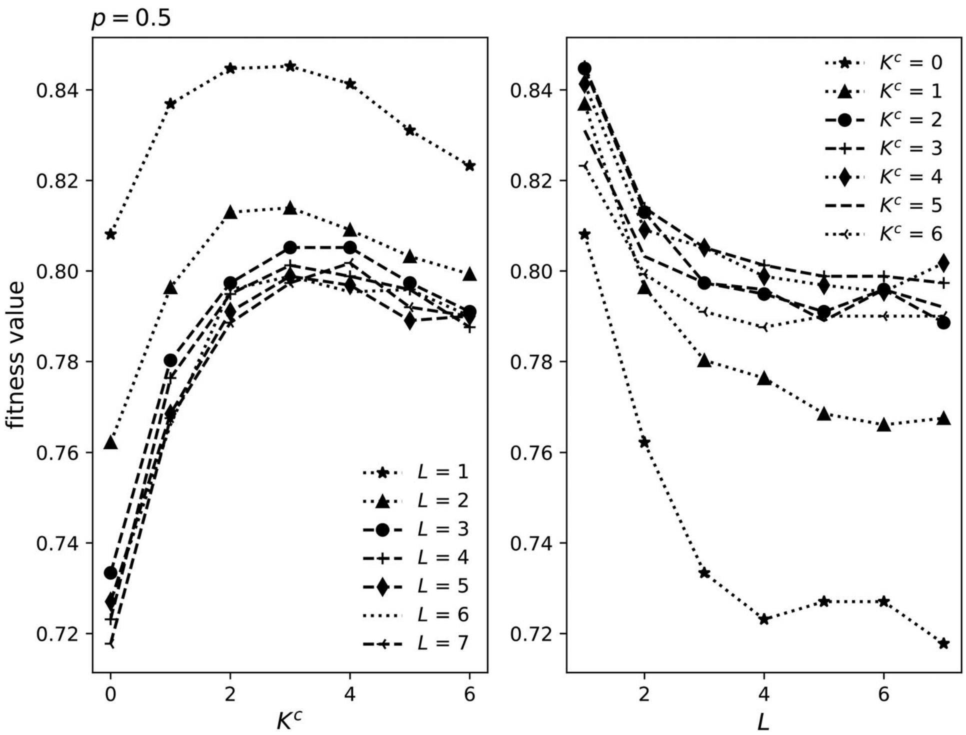

Figure 2. The results for different K^c and L based $p = 0.5$.
where $K^c \in [0, 6]$ and $L \in [1, 7]$; The time variable t takes the value 50 and the search curve tends to be smooth in this range; the fitness value of the vertical coordinate is the percentage of the current fitness to the global optimal fitness.

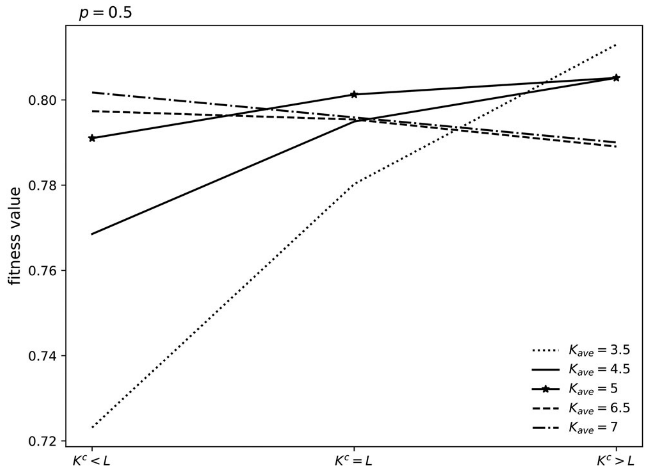

Figure 3. The results of imbalance in K^c and L under the different global complexity based $p = 0.5$.

increasing the complementarity between different types of information and meeting the differentiated needs of consumers. However, as complexity increases, the performance of co-innovation decreases. Theoretically, interaction complexity has a non-linear effect on adaptive search efficiency. As the number of local peaks increases faster than the global optimum, the difficulty of searching for better performance is greatly increased. In practice, creators should focus on more, but not necessarily on all, decision-making structures, which is similar to the findings of empirical studies (Conboy, Mikalef, Dennehy, & Krogstie, 2020). Creators should cover more attributes that may affect innovation, such as product, brand, target consumer, quality, and quantity, but should not aim to make perfect decisions in each attribute, as high complexity makes decisions so chaotic that the result is worse performance.

In addition, the dependency effect decreases the performance of co-innovation, as shown in the right panel of Figure 2. The interventions exerted by the platform on creators always make the adaptive search of creators more difficult because they increase the external complexity of the decision combination (Baum, Cowan, & Jonard, 2010). When creators have low dependency, they pay invisible administrative and institutional costs to the platform, which is reflected in diminished performance. As dependency increases, the dependency effect is marginal to performance, and administrative and institutional costs are amortised (Miric & Jeppesen, 2020).

However, two paradoxes arise. First, creators must depend on the platforms, and their independence contradicts the dependency effect. Second, in practice, many creators rely solely on one platform, rather than multihoming. To resolve these two paradoxes, further analysis was conducted by restricting the K_{ave}, and the results are shown in Figure 3.

Figure 3 shows the cases, in which K_{ave} takes values of 3.5, 4.5, 5, 6.5, and 7. Thus, the values cover different cases with low, medium, and high environmental complexities. It can be found that K^c and L play completely opposite effects on co-innovation fitness when K_{ave} is high and low, respectively. Among the low level of complexity of the entire structure of co-innovation, that is, in which K_{ave} is equal to 3.5 and 4.5, the co-innovation fitness with higher dependency effects is much lower than that with lower dependency. Content creators' decision complexity contributes more to the performance of co-innovation fitness. However, the effect diminishes as K_{ave} increases to the median value. The dependence effect is no longer almost insignificant, although there is still some negative correlation between co-innovation fitness and the medium K_{ave}. Finally, the opposite conclusion emerges when K_{ave} is greater than the median. Content creators with higher dependency effects had higher performance, and co-innovation fitness decreased when the dependency effects became weaker.

In summary, the choice of dependency or independence is strongly correlated with the complexity of the environment. In general, if all the conditions are unconstrained, then choosing full independence is the optimal way to achieve better performance. However, in most cases, external environmental constraints exist. Content creators need to consider relying on digital platforms to avoid potential market risks or to gain additional market resources. For content creators, the greater the external challenges they face, the stronger the motivation to choose dependence. This also explains the two paradoxes mentioned earlier from the perspective of organisational (Ghazawneh & Henfridsson, 2013) and environmental resources (Brunswicker, Almirall, & Majchrzak, 2019; Guinea & Raymond, 2020).

To ensure the robustness of the results, additional experiments based on different p values and different combinations of N^p and N^c were used for

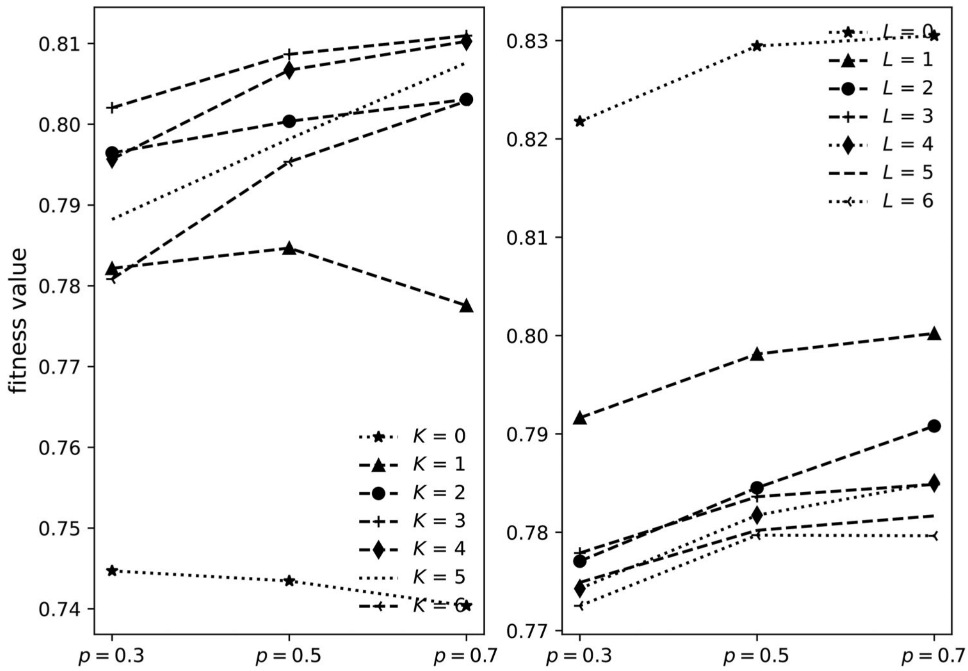

Figure 4. The effects of exploration.

sensitivity analyses, and the results are presented in Appendix B. According to the experimental results, the effects of internal interaction complexity and external dependency on co-innovation are not sensitive to these different combinations of parameters; therefore, the experimental findings can be considered robust.

In addition, the effects of exploration on co-innovation were examined, and the results are shown in Figure 4. Theoretically, when the complexity of the interaction is low, it is better to search in order rather than jumping. But except for cases with low levels of K, as p increases, it does visibly reach higher peak values of co-innovation, which is consistent with actual business and innovation laws (Abbate, Codini, & Aquilani, 2019; Bresciani, Ciampi, Meli, & Ferraris, 2021). As mentioned earlier, relying more on platforms is an effective method for creators to balance environmental risks (Park, Kim, Jeong, & Minshall, 2021; Shree, Kumar Singh, Paul, Hao, & Xu, 2021). However, higher levels of exploration can weaken this tendency toward dependency. Thus, creators utilise their own exploration to face the risks of the external environment; that is, they use risk to counteract risk. In this case, creators choose to be more dependent on the platform only when faced with an environment of the highest complexity.

4.2. Theoretical contribution

This study developed an understanding of digital platform-based decision-making and innovation processes in the OR literature. First, platforms are generally considered to play an intermediary role in reducing transaction costs and facilitating sales in the literature (Evans & Schmalensee, 2017; Wang, Li, & Yi, 2021). However, in the digital economy, platforms are seen as communities of value creation in the business ecosystem (Gawer, 2021; Mosterd, Sobota, Kaa, Ding, & Reuver, 2021). Research should concentrate on collaboration and value co-creation between platforms and complementors, where the decision-making process for co-innovation is still a crucial process for co-innovation (Ji & Gunasekaran, 2014). This study filled this gap by constructing a decision interaction network and innovation search algorithm to examine the evolutionary mechanism of co-innovation.

Second, the model developed provides a methodology for future research. The NK model and adaptive search algorithms have been widely used in computational modelling in OR, information management, and organisational management (Kapsali, Bayer, Brailsford, & Bolt, 2022; Puranam, Stieglitz, Osman, & Pillutla, 2015). Theoretically, the asymmetric NK model extends the directionality of the interactions of decision attributes and provides new insights for solving directed network problems in complex networks. In addition, this study demonstrated the effectiveness and comprehensibility of agent-based computational models for digital systems. Furthermore, this study demonstrated the effectiveness and comprehensibility of agent-based computational models for digital systems, connecting to earlier ideas in the literature (Kapsali, Bayer, Brailsford, & Bolt, 2022).

4.3. Implications for practice

The findings have proposed that both the complexity of the internal interaction and external dependence effect of content creators are important determinants of the evolution mechanism of the co-innovation of digital platforms and content creators. Independent decision-making is significant to co-innovation for content creators. As the dependency effect is the unequal intervention that platforms exert on creators, creators are forced to consider more factors when making decisions, making it harder to innovate, although the negative effects caused by the dependency effect are marginal diminishing. Instead, platforms are more willing to implement interventions to reduce potential costs (Gawer, 2021). Additionally, balancing the complexity of decision-making facilitates better co-innovation. Interactions between decisions cannot be lacking, and an appropriate increase in interaction can leverage coordinated coupling to promote co-innovation (Sedera, Lokuge, Grover, Sarker, & Sarker, 2016). However, the excessive complexity of decision combinations creates a chaotic decision landscape and structure, which increases the difficulty of innovation, leading to reduced performance.

More meaningfully, however, choosing to rely more on the platform can effectively amortise the decision risks of the external environment. A turbulent environment presents both opportunities and challenges, and a more rational approach is to increase the smoothness of innovation by relying on leading platforms. In addition, exploration effectively helped content creators break out of the local peak trap (Hamer & Frenken, 2021). These findings encourage agents to take higher potential risks of innovation, as such risks are worthwhile.

4.4. Limitations

This study developed an improved model to assess co-innovation between digital platforms and content creators, but still had the following limitations and outlook. First, the model characterises the innovation process in an abstract manner. The abstract model facilitates the understanding of complex decision-making processes; however, more precise data-based studies are still needed to provide decision support. Second, the model assumes a binary decision process for agents and ignores the possibility of multivariate decision-making. Finally, the model considered only the scale-free network structure of one platform. The structure of concurrent platforms formed by accounting for connections between different platforms deserves further attention.

5. Conclusions

This study extends the theoretical research on co-innovation based on digital platforms. First, a theoretical model with dependency effects and decision complexity is constructed to simulate a real network structure. Dependency effects are prevalent in mature and developing digital platform economies, making the model a more valid and realistic theoretical tool for subsequent researchers. It also provides a new approach to constructing directed network structures. Second, the research model assessed the long-term effects of co-innovation. This breaks away from the cross-sectional perspective-based studies that are often found in the literature (Sedera, Lokuge, Grover, Sarker, & Sarker, 2016; Wei, Wang, & Chang, 2021), although they focus more the outcome than the process of innovation evolution. Finally, a parameter of environmental complexity is constructed in the model to assess the impact of environmental effects. The literature generally affirms the impact of resource constraints and environmental uncertainty on firms' digital innovation (Shree, Kumar Singh, Paul, Hao, & Xu, 2021; Wu, Lao, Wan, & Li, 2019), but it is difficult to measure or calculate this effect. This study aims to measure the resource constraints of co-innovation evolution by including the complexity parameter of the entire environment, thus extending a new perspective to measure resource and environmental effects.

Second, this research extends the study of adaptive search in rugged landscapes based on the NK model. An asymmetric model was constructed to evaluate the directed interactions. This model provides an effective simulation of the dependency effect of the heterogeneity of content creators and a new perspective for studies based on the NK model. Based on this, future research can be extended to more diverse network structures and decision makers.

Finally, the model is also scalable. As the research model is an abstract theoretical model, it has many potential application scenarios and decision platforms in many other fields. The research model was constructed based on the scale-free characteristics of complex networks and can be extended to some extent to network structures with similar characteristics. In fact, the behaviours and decisions of many organisations, including governments, corporations, and smaller organisations, are related to value co-creation based on scale-free network structures (Barabási & Albert, 1999). Inter-group-based dependency effects and value co-creation appear to be particularly relevant to the diversification of resource agglomeration and division of labour and are particularly important in the context of management based on the rapid growth of industrial economies.

Disclosure statement

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Appendix A. Pseudo-code of the research

The model was executed according to the following pseudo-code. And in standard case of the research, the parameter was set to: $N^p = N^c = 7$ and the number of runs is 1000.

Require: (N^p, N^c, i, p, t)
  Require: $K^p \in [0, N^p-1]$, $K^c \in [0, N^c-1]$, $L \in [1, N^p]$
  Ensure: $N = N^p + N^c$
    for each L, K^C, i **do**
    initialise influence matrix $M \leftarrow (N^p, N^c, K^p, K^c, L)$
    initialise landscape data $D \leftarrow (M, N)$
    Require random decision portfolio P_0
    for each t **do**
    $F \leftarrow (D, t, P_0)$
    if conduct exploratory **then**
    Initialise new portfolio P_1
    else
    change one attribute of P_0 to get P_1
    end if
    $F_{new} \leftarrow (D, t, P_1)$
    if $F_{new} > F$
    then
    $P_0 \leftarrow P_1$
    end if
    end for
    end for

Appendix B. Results of sensitivity analysis

A series of sensitivity analyses were advanced to ensure the robustness of the experimental results. First, Figure B1 and Figure B2 shows the results with p taking values 0.3 and 0.7, respectively. The curves have the same trend compared to $p = 0.5$, an inverted U-shaped trend of K^c for co-innovation fitness and a negative correlation of L for co-innovation fitness can be observed. In sum, the effect is insensitive towards exploration.

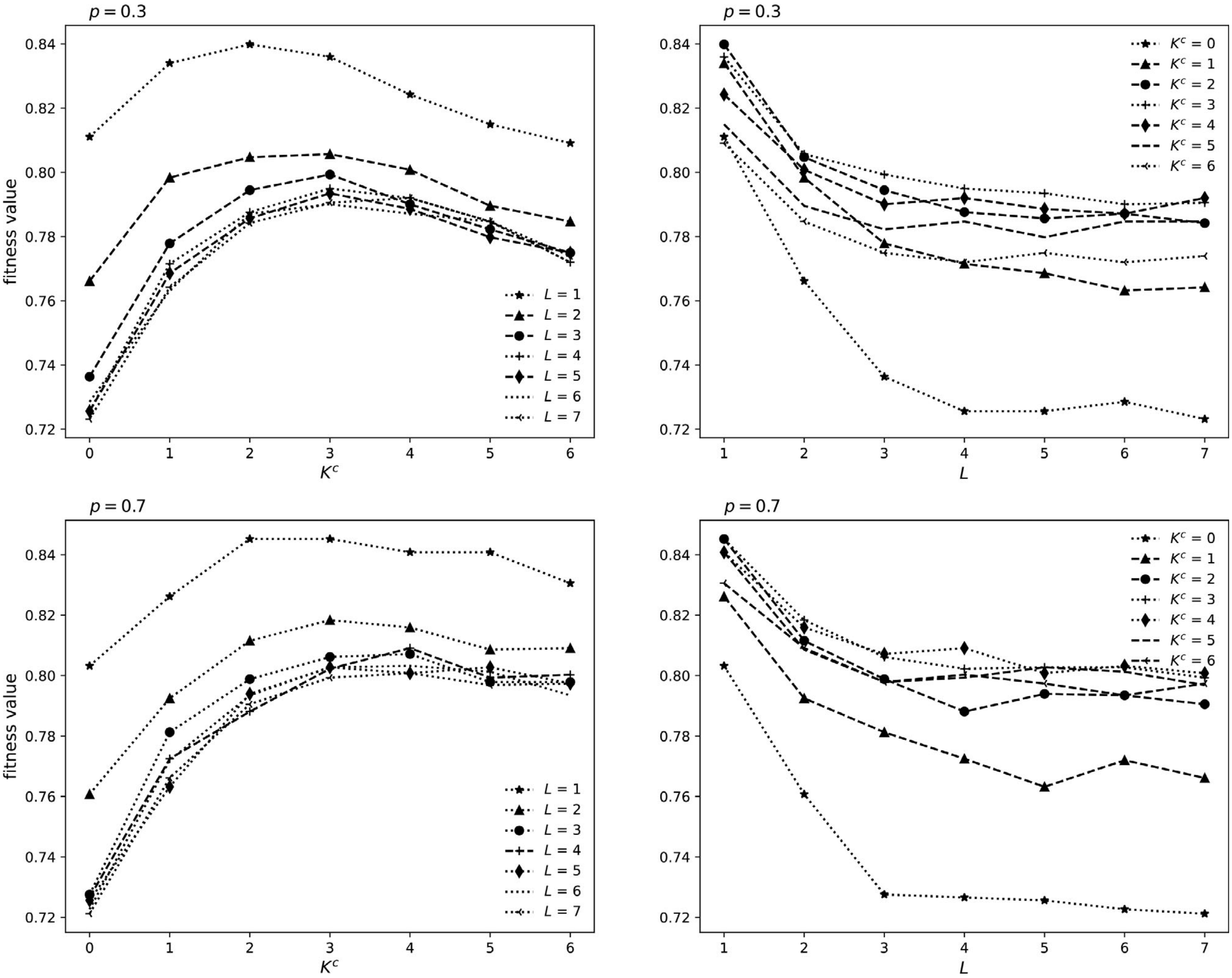

Figure B1. The results for different K^c and L based $p = 0.3$ and $p = 0.7$.

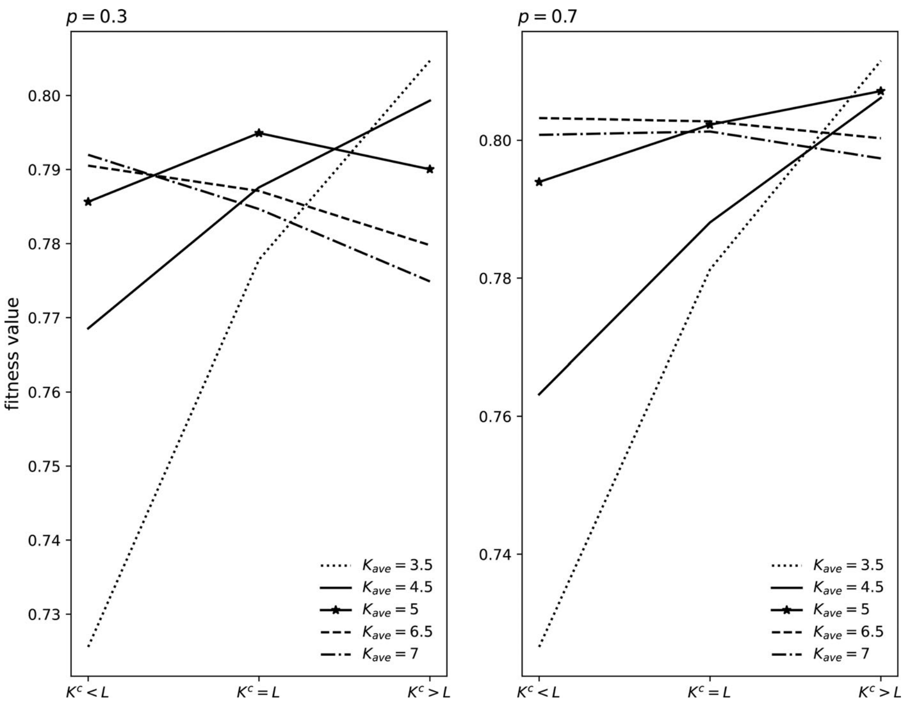

Figure B2. The results of unbalance of K^c and L under the different local complexity based $p = 0.3$ and $p = 0.7$.

Second, Figure B3 shows the results of $N^p = N^c = 6$, Figure B4 shows the results of $N^p = N^c = 8$ to examined the sensitivity based on different N. The findings are in line with the literature in that the experimental results are not sensitive to the value of N.

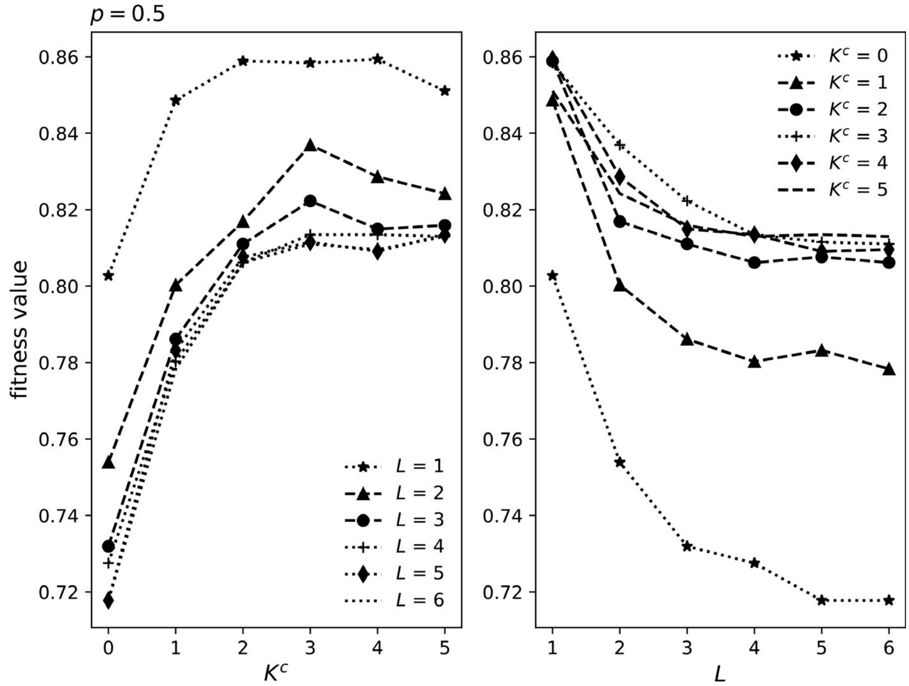

Figure B3. The results for different K^c and L based $N^p = N^c = 6$.

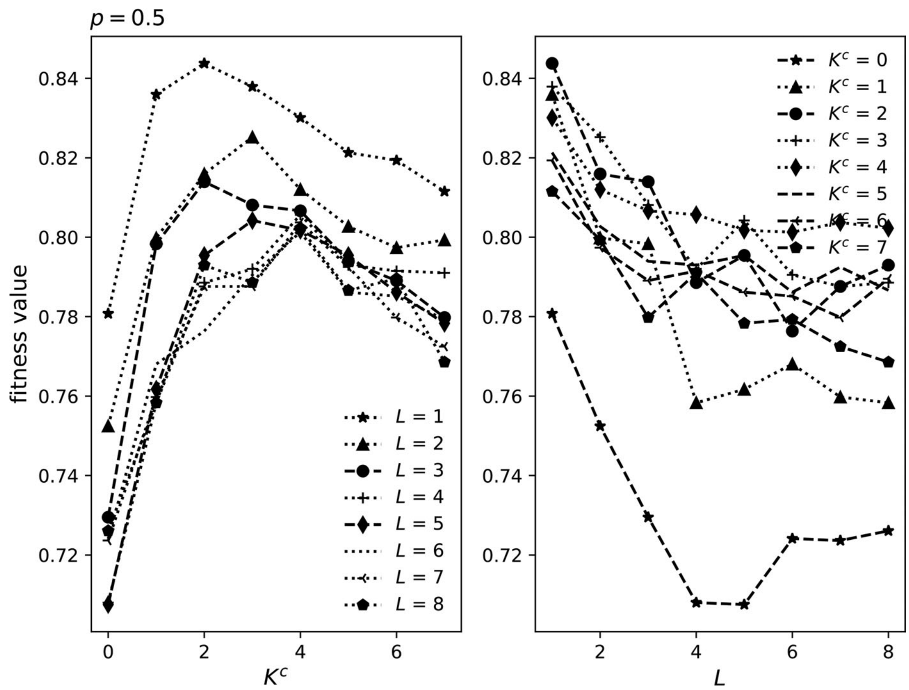

Figure B4. The results for different K^c and L based $N^p = N^c = 8$.

Finally, Figure B5 and Figure B6 report the results with unequal N^p and N^c, which are $N^p = 5$ with $N^c = 9$, as well as $N^p = 9$ with $N^c = 5$. The results showed that tuning different combinations of N^p and N^c, while keeping N constant, did not have a significant effect on the experimental results.

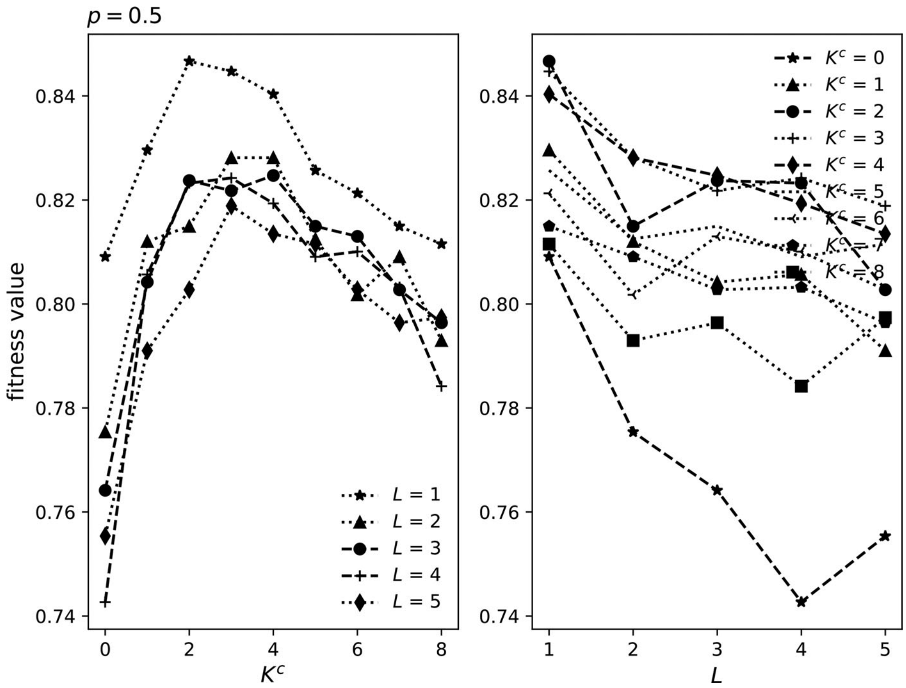

Figure B5. The results for different K^c and L based $N^p = 5$ and $N^c = 9$.

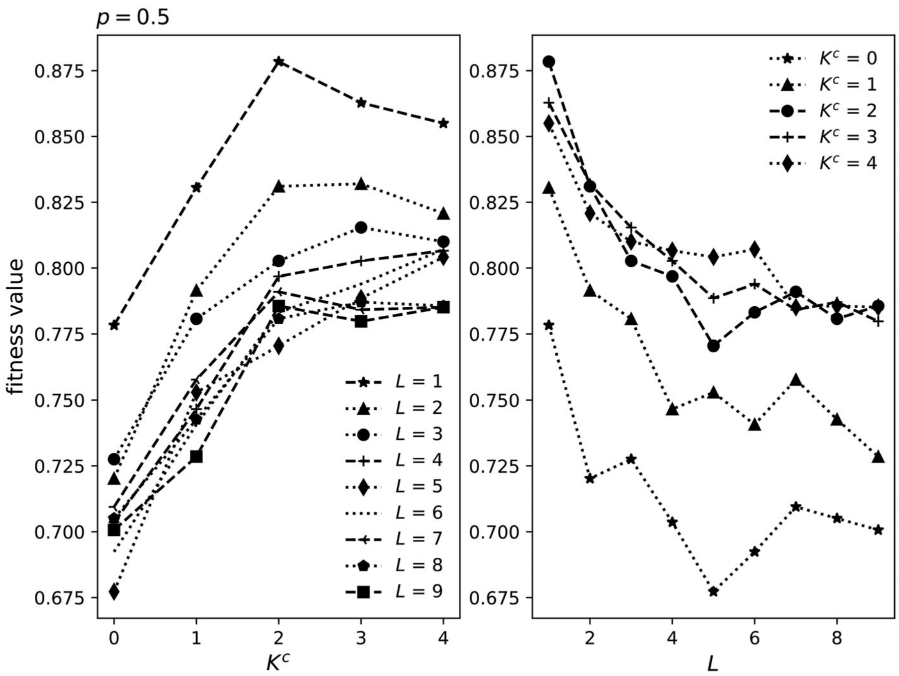

Figure B6. The results for different K^c and L based $N^p = 9$ and $N^c = 5$.