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OI moves in SMEs. Pathways to success

Antonios D. Livieratos*

National and Kapodistrian University of Athens, Department of Business Administration, Sofokleous 1, Athens 10559, Greece.
E-mail: alivieratos@ba.uoa.gr

George Tsekouras

University of Brighton, Centre for Change, Entrepreneurship and Innovation Management, Mithras House, Lewes Road, Brighton BN2 4AT, United Kingdom.
E-mail: G.Tsekouras@brighton.ac.uk

Wim Vanhaverbeke

Surrey Business School, Alexander Fleming Rd, Guildford GU2 7XH, United Kingdom.
E-mail: w.vanhaverbeke@surrey.ac.uk

Georgia Tsiliki

ATHENA Research and Innovation Centre, Institute for the Management of Information Systems, Artemidos 6 & Epidavrou, Marousi 15125, Greece.
E-mail: gtsiliki@athenarc.gr

Abstract: The paper is building on the 'OI move' concept developed to disentangle the OI journey. OI moves represent identifiable OI activities in a SME and two of the most important aspects of an 'OI move' are knowledge inflows (*who is the SME innovating with?*) and knowledge outflows (*who is exploiting the result?*). Knowledge inflows can be carried out with a variety of partners while knowledge outflows can be delivered through various exploitation models. Combining all these options forms a typology of 24 types of OI moves discussed in another paper (Livieratos et al., 2020). However, not much is known about the sequence of OI moves that form 'pathways' leading to successful innovation and business outcomes. To this end, the aim of the study is to define patterns of successful OI pathways for SMEs.

The study is based on a dataset of 500 OI moves extracted from 106 case studies of European innovative SMEs. The sequence of the OI moves in each SME, and the success score of each OI move were analyzed using machine learning techniques (association analysis), resulting to 32 rules of successful OI pathways of SME presented in the form of a directed graph.

Main findings up to this point indicate that four OI moves play a major role in forming successful OI journeys: collaboration with R&D service providers, with complementary partners and with customers and users, all of them associate with internal exploitation. These four OI moves have a mutually reinforcing effect, with a virtuous cycle leading to more success over time. The identified successful OI pathways provide practitioners with a 'recommended rule of thumb' when selecting the next OI moves based on OI journeys that have worked well for other SMEs.

Keywords: Open Innovation; SMEs; Machine Learning; Open Innovation Move; Business Strategy; Multiple Case Study; Association Analysis

1 Problem

Innovation activities, in most SMEs, take place in the framework of a few ‘unstructured’ innovation projects (Nada, 2012) since most of them have neither an organizational structure for innovation (*e.g. a dedicated R&D department*), nor permanent resources (*e.g. constant R&D budget*) assigned to this task (Vossen, 1988). As SMEs are opening-up the innovation process, innovation activities resemble less to a well-planned project and more to a long ‘journey’ (Vanhaverbeke, 2017). This ‘open innovation journey’ is full of unforeseen challenges and unexpected ‘turns’, some of which are related to the SME’s inherent limitations (e.g. their limited resources), some of which are related to developments outside of their control (e.g. changing strategies of more powerful partners such as large multinationals). As a result, SMEs need to carefully manage their Open Innovation (OI) ‘journey’ (Brunswicker and Vanhaverbeke, 2014), if it is to deliver results and generate value for themselves. However, as of today, academic literature provides very little insights as to the various ‘steps’ involved in these long OI ‘journeys’ and more importantly to the sequence of these steps that deliver for the relevant SMEs. Questions like “*what is the right next step for an SME’s OI ‘journey’?*”, given the steps it has been already involved to, have not been addressed by the current state of the literature.

2 Current understanding

The 'OI move' is a concept developed to disentangle the OI journey in different steps (Livieratos et al., 2020). Two of the most important aspects of an OI move are knowledge inflows (*who is the SME innovating with?*) and knowledge outflows (*who is exploiting the result?*) – see Table 1. In relation to knowledge inflows an SME can innovate with: R&D service providers (Huggins et. al 2019), complementary partners (Gassmann and Enkel, 2004; Livieratos et al., 2020), customers (Debruvne, 2014), suppliers (Henke and Zhang, 2010), (non-paying the focal firm) users (Brunswicker and Vanhaverbeke, 2014), competitors (Gnyawali and Park, 2009), communities (West and Lakhani, 2008) and/or the crowd (Christian, 2019). In relation to knowledge outflows an SME may exploit the result of a collaborative innovation activity in the following ways: it can use the knowledge internally, co-exploit it with a partner or leave the exploitation to the partner (Chesbrough, 2003). Combining these two options yields an 8 by 3 matrix forming a typology of 24 types of OI moves for SMEs pursuing open innovation (Livieratos et al., 2020).

Table 1. A typology of options for SMEs aiming to (open) innovate

Knowledge outflow / Knowledge inflow	Internal Exploitation	Co-Exploitation (with a partner)	External Exploitation (via a partner)
R&D service providers	**1**	**2**	**3**
Complementary partners	**4**	**5**	**6**
Customers	**7**	**8**	**9**
Users	**10**	**11**	**12**
Suppliers	**13**	**14**	**15**
Competitors	**16**	**17**	**18**
Crowd	**19**	**20**	**21**
Community	**22**	**23**	**24**

Source: Livieratos et al. (2020)

3 Research question

Using this typology as a coding framework, previous research discussed the incidence of different types of OI moves used by SMEs in their OI journey (Livieratos et al., 2020). However, not much is known about the sequence of OI moves, which is the pathways of successive OI moves that lead to more successful innovation outcomes. The aim of the current study is to define patterns of successful pathways in OI journeys of SMEs.

4 Research design

The research is based on 106 in-depth case studies describing the OI journey of innovative SMEs from 19 European countries that were the object of a large-scale research project (INSPIRE SMEs EU research grant No 691440). The above-mentioned typology is used as the coding framework of OI moves: based on close observation of that 106 SMEs we generated a dataset of 500 OI moves and their sequence for each of the investigated case studies. For instance, the sequence of OI moves for Pulp Eye (Sweden), one of the case studies, is the following: 2 (innovating with R&D service providers, leading to Co-exploitation) → 17 (innovating with competitors, leading to co-exploitation) → 4 (innovating with complementary partners, leading to internal exploitation) → 7 (innovating with customers, internal exploitation).

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Table 2. The OI journey of Pulp Eye (Sweden)

Knowledge outflow / Knowledge inflow	Internal Exploitation	Co-Exploitation (with a partner)	External Exploitation (via a partner)
R&D service providers	1	2	3
Complementary partners	4	5	6
Customers	7	8	9
Users	10	11	12
Suppliers	13	14	15
Competitors	16	17	18
Crowd	19	20	21
Community	22	23	24

For each of the 500 OI moves, the case studies' authors were asked (1) to verify that these were correctly positioned in the coding framework (typology), (2) to give the sequence of the OI moves and (3) to assess, using a 9 point Likert scale (with 9 being ‘extremely successful’ and 1 being ‘extremely unsuccessful’), how successful each OI move was (from the SME point of view).

The collected data (500 OI moves positioned in the coding framework, the success of each OI move and 106 OI journeys portrayed as sequences of OI moves) were analysed using machine learning. More specifically, association analysis (Zimek et al., 2014; Zijian et al., 2001) was applied to find links between the typology steps and statistically significant connections of journeys with at least two OI moves. Association analysis is a data mining technique that discovers connections between specific objects (Yin-Fu and Wu, 2011), in this case, co-occurrence relationships among the recorded activities performed by specific SMEs. The order of appearance is also taken into account, suggesting starting points and moves thereafter to form OI journeys. The end-product is a ranked list of journeys based on their succession score and their frequency of appearance, which can then be exploited to make decisions using prior knowledge. For each of the suggested journeys a likelihood score was calculated to show how beneficial is a next OI move to the journey based on the available success scores (mean success score values were used). The suggested pathways of the OI journey were filtered by frequency of appearance in the data and success score, resulting in a final set of 32 "rules" out of 199 that were overall formed. A rule defines how a transition from (one or) a sequence of previous OI moves to another OI move leads to an increase (lift) in reported success. The threshold values used are the frequency of appearance ≥4 and the adjusted likelihood score≥1, respectively.

5 Findings

All 32 rules representing successful pathways of SMEs’ OI journeys, as these were extracted by the association analysis, are presented in Table 3. The first column shows the number of the rule, the second column shows the previous positions of the OI journey while the third column shows the recommended next step of the OI journey according to the rule. Recommendations were derived from ‘what worked well’ for the SMEs of the sample. ‘Lift’ is a statistical measure and it represents the level of success of the OI journey. Lift is the adjusted likelihood score which we set to be greater or equal to 1. The statistic ‘Count’ represents the frequency of observations supporting this OI journey. The last column in Table 3, labelled ‘Order’, shows the length of the journey with respect to how many OI moves it consists of – it is the number of OI moves in the 2nd plus one (OI move in the 3rd column).

Table 3. A typology of options for SMEs aiming to (open) innovate

No of Rule	Previous position(s)	Recommended next position	Lift	Count	Order
1	1,4,7	10	2.27	5	4
2	1,17	4	2.06	4	3
3	2	10	1.82	4	2
4	17	4	1.8	7	2
5	4,7	10	1.75	7	3
6	1,10,7	4	1.72	5	4
7	1,10,4	7	1.63	5	4
8	10,7	4	1.6	7	3
9	1,8	7	1.52	4	3
10	13	4	1.5	8	2
11	9	4	1.37	4	2
12	1	8	1.37	4	3
13	8	7	1.37	6	2
14	10,4	7	1.33	7	3
15	1,3	4	1.29	5	3
16	2	5	1.27	4	2
17	1,1	5	1.25	5	3
18	1,5	10	1.25	5	3
19	9	1	1.22	5	2
20	10,5	1	1.22	5	3
21	10	4	1.18	12	2
22	4,8	1	1.17	4	3
23	13	1	1.06	8	2
24	10,4,7	1	1.04	5	4
25	1, 10	4	1.03	7	3
26	8	4	1.03	5	2
27	4,5	1	1.02	7	3
28	No previous step	1	1	72	1
29	No previous step	4	1	51	1
30	No previous step	7	1	46	1

31	No previous step	5	1	30	1
32	10	5	1	6	2

The 32 rules may also be presented in the form of a dynamic directed graph as shown in Figure 1. The graph shows the resulting network bundling all successful OI journeys of the SMEs of our sample. The graph is comprised by:

a) **Positions** (or OI move types) deriving from the typology/coding framework (*e.g. position No 1 is 'collaboration with R&D service providers leading to internal exploitation of the result'*) and

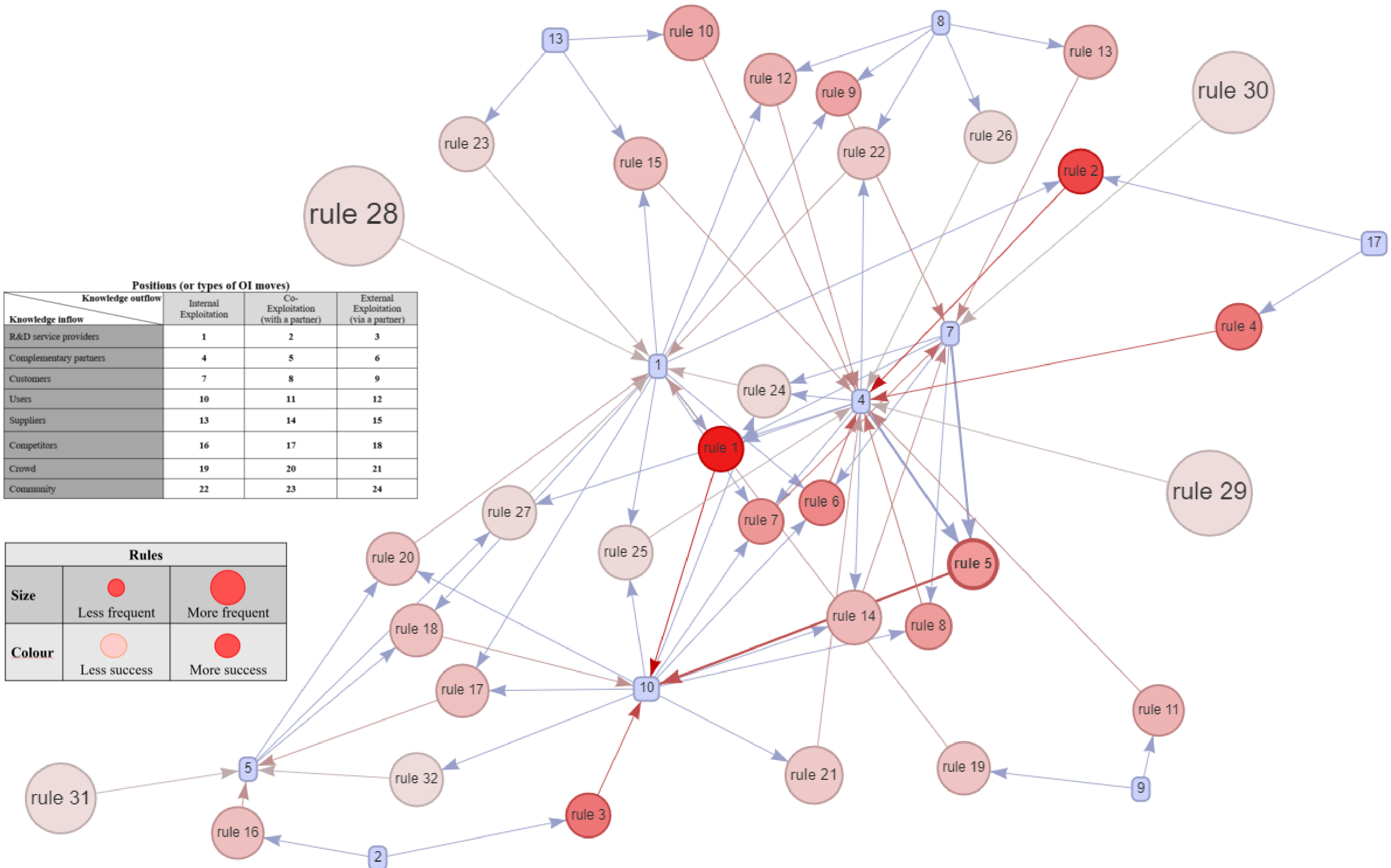
b) **Rules** that connect one or more positions to a subsequent position leading to successful OI journeys. The size of nodes (circles) depends on the frequency of appearance in the data (measured by Count), with smaller circles representing less frequent OI moves. The colour of each circle depends on the level of success of the OI journey (measured by Lift), with dark red representing highly successful journeys and light red less successful journeys.

c) **Edges** (arrows) starting from a position in the typology indicate a plausible next position and a specific direction clearly indicate plausible previous positions (as prerequisites) and next steps (ending position).

For instance, lets assume that for an innovation project, an SME has been in position 2 (innovated with an R&D service provider and the result of this partnership led to co-exploitation) and needs to decide on the next steps of its OI journey. From position 2 at the bottom of the graph two edges lead to the two associated rules of this position. *Rule#3* suggests that a plausible next position would be position 10 (innovating with users leading to internal exploitation) and *rule#16* suggests that a plausible next position would be position 5 (innovating with a complementary partner leading to co-exploitation). The color in the nodes presenting the two rules indicate that rule#3 is characterized by greater success while the size is indicating that rule#16 is based on a slightly greater frequency of appearance in the data. Similarly, if an SME intends to move to position 5 (complementary partners leading to co-exploitation) there are four associated rules. Rule #32 indicates that before moving to position 5 it is plausible to have been in position 10, rule #16 suggests that it is plausible to have been in position 2, rule#17 indicates that that it is plausible to have been in positions 10 and 1 and rule#31 suggests that position 5 could be the first OI move in an OI journey.

Note that Figure 1 comes in the form of a web application where a) rules are clickable popping-up the details of the rule (as they appear in Table 1) and b) positions are also clickable highlighting only the rules associated with the position.

Figure 1. Pathways to success for OI journeys



Positions (or types of OI moves)

Knowledge outflow / Knowledge inflow	Internal Exploitation	Co-Exploitation (with a partner)	External Exploitation (via a partner)
R&D service providers	1	2	3
Complementary partners	4	5	6
Customers	7	8	9
Users	10	11	12
Suppliers	13	14	15
Competitors	16	17	18
Crowd	19	20	21
Community	22	23	24

Rules

Size	Less frequent	More frequent
Colour	Less success	More success

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Preliminary findings indicate that:
- SMEs rely on a combination of various OI moves to pursue their OI journey, adopting various methods of knowledge inflows (*who is the SME innovating with?*) and knowledge outflows (*who is exploiting the result?*).
- Out of the ten important OI moves, four play a major role in SMEs' OI journeys: collaboration with R&D service providers, collaboration with complementary partners and collaboration with customers and users. All of them are associated with internal exploitation.
- The four OI moves that play a major role have a mutually reinforcing effect, with the possibility of a virtuous cycle leading to more success over time.
- The various successful OI pathways have different degrees of success (from the SME point of view). How to determine journeys that lead to success in innovation is a point of consideration for future research.

6 Contribution

As there is a clear need to move into more fine-grained levels of analysis when studying OI (Bogers et al., 2017), the present study provides a conceptual tool to disentangle the different OI journeys of SMEs based on the data collected. OI moves and their coding framework (typology) can provide the basis so as to better understand SMEs activities and in turn to explore patterns.

Based on a substantial quantity of data (106 OI journeys, 500 OI moves) and a framework that enables the exploration of patterns in the OI journey, our study makes a contribution in the identification of SMEs' pathways to success in OI. Recognizing OI as a sequence of related decisions provides a richer and more refined picture of how OI is successfully practised by SMEs so to deliver value for them.

7 Practical implications

Besides providing a typology presenting all possible options of an SME when conducting an OI move, the results of the present study may also provide some practical recommendations for the design of an OI journey. Based on the present research a practitioner may take recommendations regarding the next position she could follow in the SMEs’s OI journey or assess if the next planned position is likely to become a successful next step in the OI journey.

8 Feedback

As this is an ongoing research, initially we would like to have feedback on the dynamics of OI moves (forming OI journeys) and the role such dynamics play in explaining the success of OI in SMEs. Moreover, by opening-up our own innovation process we are open to suggestions as well as collaborations on the use of the current dataset leading to further research outcomes that will enhance our understanding on SMEs OI practices.

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