Iranian Journal of Management Studies (IJMS) *http://ijms.ut.ac.ir/*
Vol. 13, No. 4, Autumn 2020 *Print ISSN: 2008-7055*
pp. 763-790 *Online ISSN: 2345-3745*
Document Type: Research Paper *DOI: 10.22059/ijms.2020.299145.673994*

Does Fundraising Have Meaningful Sequential Patterns? The Case of Fintech Startups

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(Received: February 4, 2020; Revised: May 7, 2020; Accepted: May 9, 2020)

Abstract
Nowadays, fundraising is one of the most important issues for both Fintech investors and startups. The pattern of fundraising in terms of "number and type of rounds and stages needed" are important. The diverse features and factors that could stem from Fintech business models which can influence success are of the key issues in shaping these patterns. This study applied the top 100 KPMG Fintech startups' data to extract clusters and fundraising pattern using sequential pattern discovery for each cluster. This led to the extraction of seven distinct clusters using 3 different clustering algorithms from 3 to 7 different rounds of investment for each cluster. The proposed frequent patterns can assist both investors and Fintech startups to show the future fundraising pattern based on their new or current startup cluster type and the ongoing stages of development.

Keywords
Fundraising, Fintech, Venture capital, Clustering, Sequential pattern recognition.

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1. Introduction

Startups, especially the technological ones, are among the most significant drivers of the growth of developed economies and financial technologies, and Fintech startups have prominent role in this arena (Beck, Demirguc-Kunt, & Levine, 2003; Leong, Tan, Xiao, Tan, & Sun, 2016; Wagenvoort, 2003). The Fintech phenomenon is the delivery of financial products and services via technological platforms and innovative business models (Chuen & Teo, 2015; Drummer, Jerenz, Siebelt, & Thaten, 2016; Gulamhuseinwala, Bull, & Lewis, 2015). In 2015, the global value of investment in Fintechs increased by 75% and reached 22.3 billion dollars. This increase shows the importance of the place of this sector as a hot ticket item in financial services (Skan, Dickerson, & Gagliardi, 2016). However, most of new technology ventures require financial resources to develop their innovation and evolve successfully (Cable, 2010; Lamoreaux & Sokoloff, 2007; Timmons & Bygrave, 1986)and be able to encounter diverse challenges like asymmetric information, financial constraint, and capital acquisition as their fundamental and continuous difficulties (Ang 1992; Brierley, 2001; Cassar, 2004; Harding & Cowling, 2006; Narula, 2004; Westhead & Storey, 1997; Zhang, 2015) These challenges are the main impediment of the firms' growth and can lead to the failure of these ventures, especially the technology-based startups. Thus, the startups should fundraise to survive and grow (Basu & Parker, 2001; Beck, 2007; Cassar, 2004; Hoenig & Henkel, 2014).

This paper tries to discover the frequent sequential fundraising patterns of Fintechs (FSFPF) using data mining algorithms and cluster them based on their business features. Therefore, the main questions of this study are:

- What are the frequent fundraising patterns of successful Fintech?
- According to what features we can categorize these startups?
- Which patterns of fundraising are the most appropriate for each business group?

The remainder of the paper is organized as follows. In Section 2, we comprehensively review the related literature to extract the factors affecting fundraising and the capital structure of startups in general and in Fintechs ecosystem in particular. Section 3 explains the research methodology. Thereafter, having identified business features, we give in the data collection procedure according to the features of the Fintechs. Lastly in this section, we validate the data. In Section 4, the Fintechs are clustered in groups according to their business features via appropriate, selected clustering algorithms. Next, using sequence algorithm, we discover the FSFPF based on their business characteristics. Having stated their results, we conclude the obtained results and compare them with other studies on capital structure.

2. Literature and Background Review

Fundraising is the selling of a proposed design or business idea to a certain part of the market (Caselli, 2010). In spite of the previous studies, still some questions are remaining: How these funds are raised and is there a certain pattern in this regard based on the capital structure? In the following lines, we first explain the factors affecting fundraising and then we discuss the general fundraising patterns and the ones specific to Fintechs.

2.1. Factors Impacting Fundraising

Factors that can impact the fundraising process are investigated with different approaches in several studies. Shelters (2013) determined that the factors such as the number of employees as well as the amount of revenues, investment, profit, and the developing status of a product can affect the fundraising stages of a firm. The financing decisions and behaviors might be different according to the characteristics of countries, markets, startups, projects, and other factors, and we can obtain different financing patterns accordingly (Hirsch & Walz, 2011). An owner’s risk tolerance and preference (Ang, Cole, & Lawson, 2010), the intrinsic characteristics of a founder (Gastaud, Carniel, & Dalle, 2019), and the offered products and services (Roeder, et al., 2018) are among the factors that influence the firm’s fundraising and financing decisions. Also, firm’s characteristics such as reputation and experience can facilitate raising new funds (Cumming, Fleming, & Suchard, 2005). On the other hand, from an investor’s point of view, several factors, including business connections (Cohen, Frazzini, & Malloy, 2008) and entrepreneurial characteristics of the investors (Bachher, Diaz de Leon, & Guild, 1999; Clarysse, Wright, Lockett, Van de Velde, & Vohora, 2005; Franke, Gruber, Harhoff, & Henkel, 2006; Zacharakis & Shepherd, 2005) can affect the investment decisions in a business. Even, geographical parameters influence small and medium-sized enterprises financing and capital use (Harding & Cowling, 2006; Klagge & Martin, 2005). Also, the social media activities of entrepreneurs and startups can increase raising funds from investors (Alexy, Block, Sandner, & Ter Wal, 2012; Liang & Yuan, 2016). In fact, the effect of social networks on the type of funding has not been proved yet. There are some extrinsic factors of startups that impact fundraising, namely competition and investment networks. However, these two factors are not uniformly equal in the entire stages of fundraising (Gastaud, Carniel, & Dalle, 2019).

Some studies have been conducted on fundraising stages, which address the factors that impact the next fundraising rounds. These factors are performance (Kaplan & Schoar, 2005), past funding (Chan & Fei, 2015), and human capital characteristics (Zarutskie, 2010). Werth and Böert (2013) showed that the startups that raise well-connected business angels might obtain the follow-on funding rounds. Evidently, the experience of a business angel in the early stages of fundraising has also a positive relationship with better performance in follow-on rounds o fundraising and receiving successive venture capitals (Croce, Guerini, & Elisa, 2016). Bui and Bui (2019) revealed that the startups that had less traditional fundraising rounds (like venture capital) were more likely to obtain equity-based crowd-funding. Surely, it was merely observed in this type of fundraising, and so, we cannot generalize it to all fundraising types.

2.2. Patterns of Fundraising

The capital structure of a firm is a function of debt and equity combination applied by the startups to finance their assets (Coleman & Robb, 2012), that is, capital structure is an outline of the entire raised capitals of a firm. Berger and Udell (1998) first presented the theory of fundraising based on the firm’s life cycle. According to their theory, private small size startups are more inclined to use internal capitals such as the owner’s personal financing, and they prefer debt to equity if they use external sources of capital. For instance, informal funds were introduced as one of the main sources of external capitals for startups (Carpenter & Petersen, 2002), and SMEs prefer to use different types of these funds, such as family, friends, and business angels (Haron &

Ibrahim, 2016). Furthermore, business owners prefer bootstrapping as their first funds to rise during their early stages of lifecycle (Cassar, 2004; Ebben & Johnson, 2006). In line with that, Kachlami and Yazdanfar (2016) demonstrated that SMEs tend to use their profit as an internal source of capital instead of a long-term debt. Confirming the pecking order theory, Coleman, Cotei, and Farhat (2016) investigated the startups present in Kauffman Firm Surveys (KFS) and declared that startups with high net worth owners would use more equity than debt. In contrast, not all studies have been in line with the pecking order and life cycle theories. Some researchers have shown that debts (or external capitals in general) have also an essential role in the startups' capital structures in their early stages similar to other stages of development (Black & Strahan, 2002; Bulan & Yan, 2009; Cole, 2010; Cole & Sokolyk, 2018; Hirsch & Walz, 2011; Robb & Robinson, 2014) . This indicates that the capital structure theories may be inefficient in some cases, and we cannot generalize them to all businesses with different natures and diverse contexts. This study tries to bridge the fundraising pattern gap which is not studied in the previous researches through the application of sequential patterns on the top 100 successful Fintech startups of KPMG.

2.3. Fundraising in Fintech

The main funding sources of Fintechs are usually venture capitals, corporate and private investors, merger and acquisition, and IPO. Initial investors usually leave the firm in early stages (from seed to C) (Arjunwadkar, 2018). Although Fintechs are mostly established in countries with available venture capitals (Haddad & Hornuf, 2019), fundraising methods in these startups – like other startups–have different types and diverse approaches. For example, In-Residence Incubator Program is an approach that has been adopted by the financial institutions present in the Fintech area. The traditional financial institutions along with other investors in Fintechs are also financing in various ways including joint venturing with Fintechs, outsourcing Fintech services to the financial institutions, acquiring/ accelerating/ incubating, or providing venture capital (Lee & Shin, 2018). In order to examine the behavior of venture capitals in Fintech startups, Cumming and Schwienbacher (2018) investigated the fundraising patterns of 2678 startups present in the "VertureXpert" database with 747 investment rounds. They realized that the pattern of venture capitals in Fintechs have been changed after the financial crisis, and this source of capital was more prevalent in countries with weaker regulatory enforcement and countries without financial centers. The interesting point is that the limited access to loans in a country increases the number of Fintech startups in that country (Haddad & Hornuf, 2019). According to Giaquinto (2019), the atmosphere of a country can affect the Fintechs funding. They also identified that there are positive relationships among business angel and seed round capital with the next fundraising. The majority of the studies conducted on fundraising of Fintechs have not paid attention to the fundraising pattern of Fintechs. From the abovementioned studies, the following shortcomings emerged. Therefore, the research gaps are as follows.

- Previous studies have followed a general approach to capital structure and ignored the role of the firm's specific features. As mentioned before, we can't generalize these patterns to all businesses with different properties.
- The studies have been focused mainly on demographic characteristics of the owners of the startups, and they have not considered the diverse details of the firm's business models.
- There is a lack of investigation on the fundraising structure of Fintech startups, although they are of utmost importance in the economic development.

To fill these gaps, this study provides the following contributions:

- Using data mining algorithms to discover the sequential and frequent fundraising patterns of the successful Fintech startups;
- Identifying specific determinants of fundraising and capital structure using different features and details of businesses;
- Categorizing startups according to similar business features and mining fundraising patterns for different features of businesses instead of using a general approach in the capital structure of startups.

3. Research method and data preparation

The research process of the paper is explained in Figure 1. In the first phase, business features that impact fundraising and generate various fundraising patterns of Fintech firms are extracted. Then in the second phase, using clustering algorithms, the Fintech business models are clustered, and in the third phase, the proposed clusters are evaluated and the best and most eligible clusters are selected. Finally, in phase 4, the frequent sequential patterns of Fintech fundraising (FSPFF) for each cluster are identified based on the extracted business features.

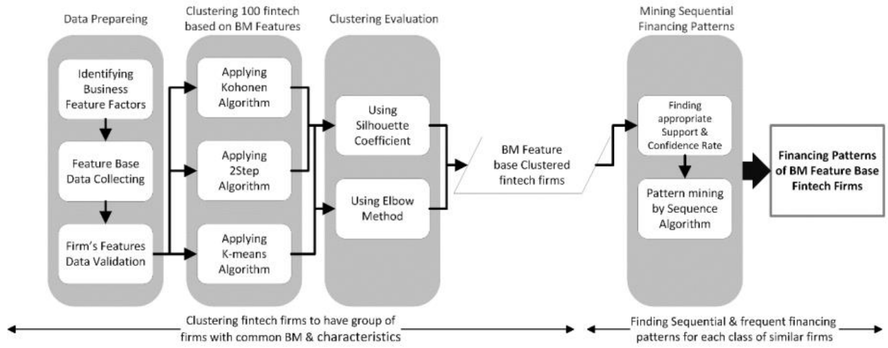

Fig. 1. Research methodology defined in four steps

3.1. Identifying Business Feature Factors

In order to present the fundraising patterns for different Fintech business models, we needed to identify the startups' features that can help us cluster them. Indeed, these features are considered as a criterion to compare the businesses and their fundraising methods. The best way to recognize a business is to examine its business model. As a result, we used the factors and features derived from business models besides other factors and firm characteristics proposed in literature to distinguish different businesses. According to Kagermann, Osterle, and Jordan (2010), a business model is comprised of four interconnected elements, including customer value proposition, profit formula, key resources, and key processes. When these features come together, they create and deliver values (Kagermann et al., 2010). Furthermore, Eickhoff, Muntermann, and Weinrich (2017) developed a taxonomy of Fintech business models which contains six dimensions, with several characteristics for each dimension. Using this taxonomy, different models of Fintech businesses are identified. Among them, we can remark payment, wealth management, crowd funding, lending, capital market, and insurance services, with each one with its specific proposed values, operating mechanisms, and business models (Lee & Shin, 2018). On the other hand, the financial technology industry is classified according to who, what, where, when, why and how fundraise them (Nicoletti, 2017) each of them considers various factors to classify Fintech startups.

Reviewing these taxonomies, we notice that the majority of the features that can create differences in fundraising patterns of different business are present in the business model of that firm. Also, there are solely differences in the classification and factor identification in Fintech business models. Table 1 presents the determinant features in the Fintech startups fundraising, so we can categorize them appropriately by the aid of these features.

Table 1. Determinant features for the classification of Fintech startups fundraising patterns

Revenue stream		**Value proposition**	**Delivery channel**	**Providing**
pay to win	Interchange Fee	Automation	Physical	customer service
Saas	commission per transaction	Collaboration	www	financial service
ownership to access	kick back	Customization	www + app	compliance service
dynamic pricing	pay per use	Insight	instant message	business service
Subscription	revenue share	matching/intermediation	Mobility	
Affiliate	Sale	Monetary	big data analytic	
razor and blades	Subscription	financial risk	IoT	
pay per use	Free	Transparency	Cloud	
Debt ratio	Hybrid	unification/consolidation	Artificial intelligence	
Servicing Fee	Freemium	Security	Robotics	
Advertising	free-in-free out	convenience/usability	social network	
Product/service		**Customers**	**Tech component**	**Innovation**
financial education	user identification	B2B	Blockchain	product innovation
Financing	care provisions	B2C	digital platform	process innovation
Investment	inform aggregation	P2P	decision support system	organization innovation
payment service	Brokerage	B2P	Marketplace	business innovation
personal assistant	currency exchange	P2B	Database	
lending/credit	current account		transaction processing system	
fraud prevention	Device			

3.2. Feature Base Data Collecting

We investigated active Fintech with all characteristics on the global scale to generalize the results of this study to all startups with similar features. Non-random sampling was used to select members. One hundred financial technology startups including top 50 and emerging 50 in 2017 introduced by KPMG International Cooperative and H2 Ventures were selected. The comprehensiveness and dispersion of the startups in this list enables us to generalize the discovered patterns to the startups with different geographical locations, specializations, lifetime, etc. Similar studies such as Coleman and Robb (2012), Coleman, Cotei, and Farhat (2016), Cole and Sokolyk, 2018, Coleman and Robb (2011) and Robb and Robinson (2014) have investigated different samples on the data of Kauffman Firm Surveys.

Because their samples were similar or outdated, they reached similar results. Hence, due to the updated and novel data that we used in our sample, the results are distinct from the past researches.

In order to extract the data of business model features of these startups, diverse resources such as papers, news, and communicational channels of startups including websites, informational weblogs, applications, software, Techcrunch, Crunchbase, Pitchbook along with all subjects published regarding any of these startups were investigated. The reliability of this information and resources was a main criterion. Thereafter, we extracted other data such as the investor type with its name, type of funding, and capital amount from Crunchbase and Owler platforms. The fundraising pattern of each firm was comprised of at most 10 fundraising rounds that were arranged according to their incidence time so that the time dependence of fundraising stages was met.

3.3. Firm's Features Data Validation

In order to validate the data and improve its quality before processing, we sent it to academics and experts of financial services industry. This way, the data were revised based on their suggestions and got eligible for processing and achieving the research purpose.

Also we took further steps to prepare data for processing. Since there was data deficiency in some features; i.e., it was impossible to obtain and extract data related to specific features of a firm, we needed to define these deficiencies. In some cases, a firm did not generally have a data record but in some other points, the reasons for the lack of data were the unavailability of sufficient data, the scarcity of the firm's information regarding that feature, or the uncertainty in choosing a proper feature. Thus, we decided to define these points as missing values.

4. Analysis

In this section, the Fintech startup datasets will be analyzed using different algorithms to mine the fundraising patterns. In the first step, we utilized different clustering algorithms to categorize startups based on their homogeneous business features. Then we examined the generated clusters and selected the most proper clusters. Finally, the sequential fundraising patterns of the top 100 Fintech startups were extracted.

4.1. Clustering of Fintechs

Clustering has been used extensively in marketing research and planning as well as market segmentation (Myers, 1996). In this study, the clustering is done using Kohonen, k-means, and two-step algorithms. Each of these uses its own computational method and algorithm to cluster the cases according to proximity and similarity**.**

4. 1. 1. Applying Kohonen Algorithm

Kohonen (2001) gives in an unsupervised learning neural network. This method takes the input vectors and performs a spatial clustering to categorize similar records. The most appropriate input data for the Kohonen algorithm is data with scored features.

We investigated 480 models using SPSS modeler software. For the width of the models, we used 9, 10, 12, 20, and 23, and for their lengths we applied 2, 3, 7, and 10. The learning rate decay was considered linear. For the first phase, we used 2, 3, 4 as the neighborhood and 0.5, 0.6 as the initial eta until the algorithm perceived general data structure. In the second phase, the neighborhood and eta were set lower so as to specify the center of clusters accurately. In line with that, the cycles in both phases were 20 and 150, respectively, as the more cycles in second phase, the more appropriate clusters would be.

In order to achieve better results, only the models that had the following conditions were selected for further investigations: the Silhouette coefficient above 0.2, more than two and less than 30 clusters, the size of clusters in minimum and maximum conditions equal to 2 and 90, and the ratio of the smallest cluster to the largest one more than 0.1.

4.1.2. Applying 2-Steps Algorithm

The two-step clustering method is a scalable clustering analysis algorithm that has been designed for large datasets. This algorithm can be implemented on both continuous and categorical data. When the record is scored in the two-steps model, it is allocated to the closest cluster. Then, the distance between the record and each cluster is calculated, and the cluster with the least distance is selected. To investigate several numbers of clusters, we used clusters with different sizes to examine the results of different models according to the number of clusters. To measure the distances, we employed Log-likelihood measure. Since the input data were mostly categorical, this measure would be more effective. The clustering criterion was the Bayesian Information Criterion, though there were no differences in the results of the studies that had applied the Akaike Information Criterion.

4.1.3. Applying K-Means Algorithm

K-means is a clustering method to group records according to the input similarity. The main idea behind it is finding k clusters where the records inside each cluster are similar to each other and distinct from the records of other clusters. K-means is an iterative algorithm, i.e., initially a set of clusters is defined and updated recurrently until no improvement is gained. To employ k-means, you need to specify the number of clusters in advance. After multiple models of empirical testing, the most proper cluster numbers were determined from the intervals of 2-12 and 15 to 20. The number of clusters and the size of the smallest cluster were limited to be up to 2. To increase the obtained clusters, we skipped over constraints similar to the Kohonen algorithm.

4.2. Clustering Evaluation

In this subsection, clustering evaluations are discussed.

4.2.1. Silhouette Coefficient

To evaluate the performance of clustering algorithms and select the most appropriate clusters, we employed the silhouette coefficient. The silhouette coefficient mixes the concepts of cluster cohesion (the ordering of models that have clusters with strong cohesive connections) and cluster separation (ordering of models with the most separated clusters). The silhouette coefficient and its interval mean ranges from -1 (indicating a very weak model) to 1 (indicating the best possible model).

4.2.2. Elbow Method

Silhouette coefficient alone is not a sufficient criterion for clusters evaluation. To determine the proper number of clusters, we employed the elbow method in the k-means algorithm, which requires choosing the cluster numbers before the clustering procedure. Indeed, in this method, the Euclidean distance between sample points in every cluster and its centroid is used to obtain the number of clusters. The sum of squared errors (SSE) is a performance measure for this method. By obtaining the SSE of each K cluster, we approximated the number of proper clusters. As SSE decreases rapidly, an approximate point that distinguishes the number of real clusters is chosen between two Ks (Yuan & Yang, 2019). Accordingly, to find a proportionate K, we calculated SSE for K from 1 to 13. The SSE values are shown in Figure 2:

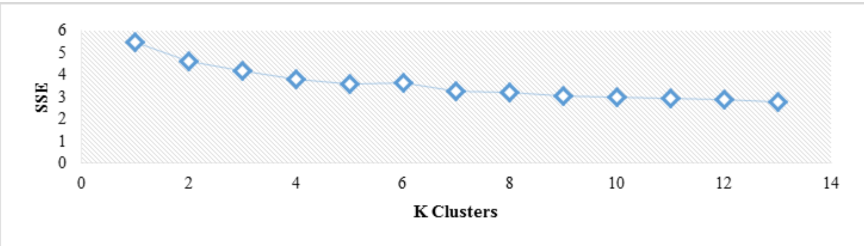

Fig. 2. Sum of squared errors (SSE) for the clusters and Elbow shown nearly at cluster 7

As it is shown in Figure 2, an elbow was formed at point 7. By exploring the sum of squared error of point 7, we realized that as the distances declined from 6 clusters to point 7, SSE decreased uniformly but after this point, increasing the number of clusters, didn't reduce SSE significantly. Thus, we selected 7 clusters as the proper cluster number for k-means clustering since it had the best conditions.

Herein, we selected the proper clustering results of all three implemented algorithms to use it in fundraising pattern mining. The clustering results of the Kohonen algorithm included models possessing the silhouette coefficient less than 0.3 and non-symmetric clusters. Also, the result showed relatively large number of clusters. Therefore, the clusters of this algorithm were improper. However, the results of the two-steps clustering had a silhouette coefficient of 0.4, which demonstrated partitioned dataset. However, the number of the clusters was 15 and also the smallest cluster included two startups, which revealed non-appropriate clusters. Besides, we had to consider that the input data of the two-steps algorithm were mostly nominal, and its obtained models enjoyed less reliability and high levels of probability error. On the other hand, except for the silhouette coefficient, there wasn't any other criterion for selecting the proper clustering in this algorithm. The results of the k-means clustering had a silhouette coefficient of 0.3 (which is acceptable), and a symmetrical cluster size when there were 7 clusters. The smallest and largest clusters included 6 and 22 firms, respectively, and the size ratio of the smallest cluster to the largest one was 0.27. Therefore, we decided to select the clustering conducted by the k-means algorithm. We classified 100 Fintech startups into 7 groups based on the similarity of business features and characteristics to discover the frequent and sequential fundraising patterns of each group in the next phase.

4.3. Mining Sequential Financing Patterns

After clustering the Fintech startups according to their business features and traits, the next step was to discover the most frequent and sequential patterns of fundraising in each cluster. Since the obtained patterns in pattern mining merely show the most frequently occurred input data, the measurement indices of these patterns are also based on their repetition. The two criteria for measuring these rules are the support and confidence (Hipp, Güntzer, & Nakhaeizadeh, 2000). Indeed, support is the ratio of the discovered rule incidence over the whole existing rules. Confidence is the ratio of the discovered rules to the discovered rules that have that precondition. Determining the minimum value of support and confidence is also necessary for discovering the most frequent patterns. Since there is not any certain criterion for determining the minimum value of support and confidence, a suitable method is to specify multiple minimums and examine them in discovering the rules. On the one hand, we don't want to have a large number of meaningless rules, and on the other hand, we don't want to lose efficient rules (Liu, 2011). After repeated tests and lots of investigation, we determined the 25% interval as the minimum value of support and confidence. However, this value varied during the implementation of algorithms, and in some clusters, we considered smaller coefficients to discover more useful patterns. Thus, based on the features of each cluster, as well as the variety of its fundraising patterns, the coefficients were even decreased by 10%.

4.4. Results

In order to understand the discovered fundraising patterns of each cluster, first we will take a look at the developed clusters. There were 13 Fintechs in the first cluster, 12 of which were payment Fintechs, with the other one being active in the banking area. Four out of 13 had completely gone through the 10 fundraising rounds. The geographical gamut of this cluster covered all points. Due to the diversity of the business features and high revenue, we named this cluster the "wealthy payments." All 16 startups present in the second cluster were active in lending business. They all used digital platforms, databases, and decision support systems as their main technology component. The web was their main product delivery channel, and the second transfer channel was data analysis. They generated revenue from the interest rate of loans and their service provision. All of the startups of this cluster were financial service providers, and all still remained private startups except for one. Therefore, the "digital lenders" was the best expression to describe them. The third cluster, the smallest one in terms of size, contained 6 startups that were active in the wealth management, payment, and lending sectors. Their major innovations were in their products and many of them had had fundraising rounds up to three.

The fourth cluster contained 16% of the total population. They were small size startups since 13 of them had employee numbers between 11 and 50. Their products and services were offered in the B2B platform. As many of these startups were small in size, the revenues of many of them were between one to four million dollars per year. In this regard, they mostly raised funds up to three or four rounds. Considering customers and the different features of the startups, the term “Fintech’s B2B diversity” was used to describe this cluster. The fifth cluster had 14 members, all of which had been established between the years 2012 and 2015. All these startups had employed digital platform and the transaction processing system for their main technological components. For this reason, the proposed value of 90% of them came from the convenience and unification of the product, which mainly were provided to customers via web and applications. Contrary to the previous cluster, whose customers were businesses, all customers of this cluster were individuals. “Web & App to consumers” was applied to describe the features of this cluster.

The sixth cluster was the largest one. It had 22 Fintech startups, all of which being active in the wealth management, lending, payment, and banking sectors. Regarding their business model, they usually generated revenue from the interest rate of loans and their service provision. Their main products and services were brokerage and lending/creating credit. In this regard, except for one case, the others were providing financial services. We named this cluster the “Loan & Service Fee Streamers.” The seventh cluster included the youngest startups whose average establishment year was 2014. This cluster contained 13% of the startups. The majority of the startups of this cluster were active in the insurance sector and many of them adopted databases and decision support system for their main technology component, concerning innovation in their products. All these startups also used web, big data analytics, and artificial intelligence as solutions for delivering their products. Their competitive advantage was in customer services. Thus, this cluster was entitled “Young Insurtechs.”

Forty-one rules were obtained from analyzing the fundraising patterns of the top 100 Fintech startups of the first cluster. The lower bound of the confidence and support values of these rules were 25%. The first cluster had the most complex capital structure among all clusters, and several patterns were discovered from it. The presence of the Series D and E indicated numerous fundraising rounds which revealed that the startups were in their last stages of development. Interestingly, in these rounds, venture capitals were present in all of the frequent series rounds, even in the seed round. Therefore, it was the most frequently used fundraising method of the startups of this cluster. This is in contradiction with some previous findings regarding the lack of venture capital in startup or in the early stages of a firm. Although the seed round were not frequent in this cluster, it recurred in 36% of the patterns, and the angels and venture capitals were the main fundraising methods of this round. They were used individually in some startups or together with some other methods. In addition, numerous startups in series A round had similarly raised funds. However, the business angel was not among the frequent fundraisings methods of the next series rounds, although the venture capital was still recurrent in the fundraising sequences. In the series B, equity was also frequent which widely employed individually or collectively in this round. In the last rounds, the venture capital was the only frequent method. Besides these rounds, there were also venture rounds and debt round. The presence of these in the consequents after the Series A showed that these rounds, especially the debt round, were mostly frequent after the early stage of a venture, and they were one of the recurrent financings in this cluster. However, in the rule 'if venture round, then debt round', we could notice that the venture round was mostly observed in the patterns, and the debt round was frequent after this round in half of these patterns. One of the frequent patterns was the venture capital in the series A, B, and C. Later, they ended to the venture capital in the series D and E, or the venture or debt round.

The second cluster was also analyzed with the same confidence and support values. By reducing the support ratio to 20%, we could obtain 53 rules with the majority being redundant and previously discovered in other rules before. In this cluster, we noticed the importance of debt financing. It was one of the frequent antecedents with 66% support in the patterns of this cluster. Besides, the series A round recurred with support ratio more than the series B and C rounds. Similar to the previous cluster, the venture capital was one of the dominant funds of this cluster, and business angel was not found in the frequent patterns of this cluster. The reason might be that the startups of this cluster were younger than the startups of other clusters. However, the debt financing, venture capital, and equity composed the frequent funds of this cluster. The seed round, similar to the previous cluster, had less support compared to the other rounds. Herein, the venture capital outnumbered others in the seed round. In the series A round, it was again the venture capital that recurred compared to the other raised capitals. However, the capital structure of the round after the series A round changed, and so, the exclusiveness of the venture capital disappeared. As a frequent round after the series A, the debt round was employed with a confidence level of 80%. Besides debt round, the series B was also among the recurrent rounds after the series A. Moreover, the venture capital and equity were the recurrent employed capitals in this round. The venture capital in the series B round was used together with the equity in some patterns, with its support coefficient being 33%.

In the third cluster, that is the smallest cluster of the top 100 Fintech startups, we used the support value of 15% and the confidence level of 25% to discover more rules. We observed that the most frequent rounds were recurred until series B. In fact, just one rule with series C round antecedent had been found with the support value of 33%. However, unlike the previous cluster, there was no sign of the recursion of the debt round in this cluster. The seed round with 33% support had frequent venture capital and business angels. The next round was series A, in which equity recurred many times (in addition to the previous round capitals). However, no rule with equity antecedent was discovered in the range of coefficients. Besides, the rule 'if venture capital, then venture capital' and 'if business angels, then venture capital' with 100% confidence indicated the numerous recursion of these two funds compared to the equity. In the series B round, we just discovered business angels and venture capitals. In the series C round, the business angels were not found among the frequent funds, and equity besides the venture capital formed the main capitals of this round. The dominant types of funding in this cluster were business angels, venture capitals, and equity with a smaller support coefficient. Meanwhile, the venture capital existed in all rounds, and the business angel was merely absent in the last round.

Although the startups in the fourth cluster were relatively inordinate, we discovered only seven rules in the fundraising patterns, even by decreasing the support and confidence coefficients to 15% and 20%, respectively. This demonstrated that this cluster had a high variety in fundraising, and there were few recursions in terms of fundraising patterns. The frequent fundraising rounds of this cluster were Series A, venture round, and seed round. The series B round was also discovered once as one of the consequents. In the seed round of this cluster, venture capital was the solely frequent fund. In line with other clusters, we found equity as the frequent fund, and the venture capital of series A ended to the venture capital and equity of the series B. The recursion of venture capital in this cluster, however, was not only specific to these rounds, but the startups of this cluster also extensively employed venture rounds, compared to other rounds, to the extent that the support coefficient of this round reached 60%. The venture round had two rules which ended in the venture capital of the Series A with 44% confidence, or another venture round with 55% confidence. The placement of a venture round as an antecedent for the Series A round demonstrated that the venture capital was also employed among the startups even before series A round in the startup or the early stage of the venture development. The venture capital was successively observed among three rounds of seed, series A, and series B, and the venture round accompanied these rounds in the pattern.

The fifth cluster had 46 rules and entailed the most frequent fundraising patterns. The discovered patterns continued up to the rounds of the Series D and E and the number of fundraising rounds was high, which seems to be natural due to the youngness of the startups of this cluster. In the first round, besides the seed round, the angels round was also frequent among the startups of this cluster. This case was not seen in other clusters. The seed round included frequent venture capital. Both the angels round and the venture capital of the seed round were antecedents in using venture capital in the series A round. Conversely, patterns such as 'if Seed round VC > Series A VC > Series B VC, then Series D VC' revealed that the startups of this cluster received more fundraising rounds by raising venture capital in the seed round, and, in some cases, their fundraising continued until the Series D round. This pattern could indicate that the startups that employ venture capitals in the seed round probably have more fundraising rounds. Both frequent rounds at the early stage ended to the venture capital in the next round. The series B round, similar to the

Series A, possessed venture capital and business angles both separately and jointly. Interestingly, there was a combination of business angels and venture capitals in both Series A and B, neither of which had any antecedent. However, they appeared as antecedents for venture capital in the next round. Besides, the business angel in these two rounds recurrently ended in the venture capital in the next round. However, in the last rounds of fundraising, only venture capital recurred, and we merely discovered this type of funding in the series C to series E rounds. The 'if Series C VC > Series D VC, then Series E VC' rule showed that the rounds with venture capitals numerously recurred at later stages of venture. Unlike previous clusters, the equity and debt financing were not in the discovered patterns of this cluster, and the business angel existed even in the series B round.

The sixth cluster was the largest in terms of sample numbers. It was the only cluster where the seed round was not discovered. this was probably due to the diversity of the types of funding in the seed round of the startups present in the cluster, where none of them recurred in the determined range of minimum support and confidence. However, in this cluster, the first frequent pattern began with the venture capital of series A round, and this capital recurred only in this round among the startups. However, the consequents of this capital could be different in the next round according to the obtained patterns. In the next round, there was Series B, where the venture capital was also frequent. With a confidence of 76%, ending with this capital was very likely. However, the presence of the rules 'if Series A VC, then Venture Round' and 'if Series A VC, then debt round' demonstrated that the venture round and debt round recurred after the Series A round. Having the 'if Series A VC > Series B VC, then Debt round' rule in mind, we noticed that the debt financing enjoyed more confidence after the Series B round, and its recursion in that situation was mostly carried out by the startups. However, with this single pattern, the venture round showed that it was used after the Series A round. The debt financing had also a successively rise, and having occurred, in some cases it was obtained in the next round, too. On the other side, the round after Series B, i.e., Series C, in which the venture capital (similar to the previous rounds) was the frequent capital raised in this round. However, in the last rounds, fundraising was not limited to venture capital only. That is, the series D round had also frequent equity and a combination of venture capital and equity funding, while in the series E round, equity was frequently obtained, too. Noticeably, this cluster showed that equity funding which was obtained in the series D round led to the venture capital in the follow-on round. On the contrary, some patterns showed rising equity funding after venture capital in the last rounds. Most of the startups were inclined to obtain more venture capitals in the entire fundraising rounds; hence, an increase in the fundraising rounds happened. Besides, they used the venture round, debt round, and equity after the series A round, which in fact was reckoned as the growth or later stage of ventures. The debt financing with successive recursion was also of utmost importance. The equity funding was preferred by the startups in the last phases of fundraising, as well.

In the seventh cluster, we employed the support and confidence coefficients of 10% and 15% in the modeling respectively, to achieve a sensible number of patterns. In this cluster, we found accelerator (with a support coefficient of 11%) as well as venture capital and business angel in the seed round. However, the venture capital with a support coefficient of 35% was preferred in this round. The series A round in this cluster had diverse frequent funds such as venture capital, equity, and business angels, and the rules including accelerator and angel antecedents in the seed round ended solely in the venture capital in the series A round. After the seed round, the capital structure did not merely end in the series A round, and the frequent fundraising patterns of these startups showed that the venture round also recurred before the venture capital of round A in some patterns. However, the patterns showed more recursion of the venture capital of the seed round and series A round before the series B round. In the next stage, the venture round was also numerously obtained by the startups of this cluster beside series B round. In the series B round, the venture capital, and equity funding recurred as well, though the venture capital enjoyed a 35% support and was more preferred. The next fundraising stage could be made of two different rounds. The series C round had venture capital as well as corporate round, where the significance and recursion of the latter was similar to the former. Regarding the confidence coefficients of both rounds, their recursions were equal. Moreover, the corporate round along with the accelerator was merely observed in this cluster, although the corporate round enjoyed higher recursion coefficients. We could see in this cluster that the equity funding of a round ended in the venture capital of the next round. Although equity, accelerator, and business angel were present, the venture capital was still the frequent funding type in the rounds.

Figure 3 illustrates the frequent sequential fundraising patterns of Fintech startups that were obtained by the patterns discovered in each cluster. These patterns reveal the conventional fundraising patterns based on startups' business features and characteristics. It illustrates six fundraising stages of Fintech startups according to different clusters except for the first cluster which has a seven-stage fundraising pattern. In every stage, the round type was identified along with the raised capital type. Since every stage did not include solely one frequent round in some clusters, we also showed another recurrent

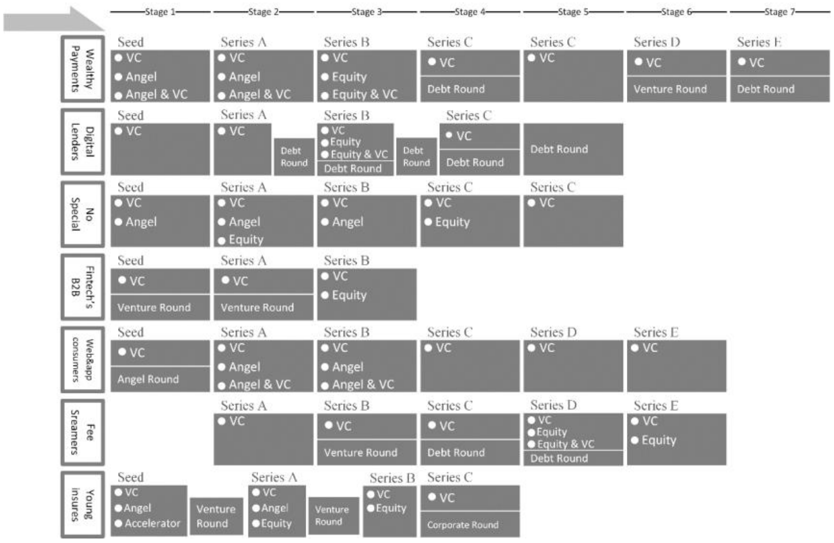

Fig. 3. The frequent sequential fundraising patterns of Fintech startups for each of the six clusters of the study

round in the patterns (if existing) in the same stage. In some of the discovered patterns in the clusters, there were some rounds between two rounds, and we did not fully display them in a phase owing to the rule discovery fewness. For example, in the pattern of the seventh cluster, we discovered the venture round after the seed round and before the venture capital of series A round. For this reason, the venture round was shown as a mid-stage between the first and second stages. The sixth cluster was not completely presented since we did not discover any frequent capital in the first stage. Obviously, there were differences in the fundraising patterns of the Fintech startups, each of which raised funds according to various features and characteristics.

5. Conclusion

The aim of this study was to fill the gap in the fundraising pattern of Fintechs discovered in the previous studies through the application of sequential patterns to the top 100 successful Fintech startups of KPMG. Therefore the frequent and sequential fundraising patterns of Fintech startups were extracted after clustering them according to similar features and characteristics. To this end, first the business features that could be employed to cluster the startups were determined. These features were different parts of business models that could impact the success or failure of a venture growth and fundraising. Investigating different business models in Fintechs (Eickhoff et al., 2017), we identified some features such as value proposition, value chain, customers, revenue stream, and financial stream as fundamental parts of business models besides business traits like the main components of technology, delivery channels, products and services, and innovation manner. In the next step, Fintech startups were clustered based on these features and were organized in different clusters which are named based on the characteristics of the Fintech clusters.

One of the observed behaviors in the patterns is that the equity in a round ends in the venture capital in follow-on rounds. We noticed in many rules of clusters that the equity antecedent in one round had just the venture capital consequent in the next round. Furthermore, almost all discovered patterns with equity antecedent revealed that the startups were not inclined to have successive equity fundraising. However, we cannot confirm this issue by just discovering this behavior and need to investigate more cases concerning the relationships between equity fundraisings with venture capital and vice versa.

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