Social network structure-based framework for innovation evaluation and propagation for new product development

Author:
Akbari, F; Saberi, M; Hussain, OK

Publication details:
Service Oriented Computing and Applications
v. 14
Chapter No. 3
pp. 189 - 201
1863-2386 (ISSN); 1863-2394 (ISSN)

Publication Date:
2020-09-01

Publisher DOI:
https://doi.org/10.1007/s11761-020-00289-8

Noname manuscript No.
(will be inserted by the editor)

Social Network Structure Based Framework for Innovation Evaluation and Propagation for New Product Development

Fateme Akbari · Morteza Saberi · Omar K. Hussain

Received: date / Accepted: date

Abstract Evaluating the innovation of a new idea before its implementation is a complicated but important phenomenon as it plays a critical role in the success of a product. The literature widely uses sentiment analysis as a technique for product designers to ascertain users' opinion towards an idea before its implementation. However, that technique focuses only on determining the opinion of users studied. It does not assist designers in providing insights in terms of what needs to be done to propagate the popularity of the idea further to ensure its success. One framework by which this can be done is by considering social network structure and representing users as nodes of that network. In this paper, we investigate how a social network structure can be used to influence a user's opinion among the society. Our proposed framework consists of four main components, namely data collection, sentiment extraction, budget approximation and presentation. After gathering customers' comments in the data collection phase, the opinion of users who have expressed it is analyzed in the sentiment analysis phase. The budget approximation component then determines the cost of spreading positive opinion among the network of users, including those who have not given it. For that, influence maximization is used to compare the cost of convergence of the general opinion of society in the direction of innovation. In presentation component, the comparative information will be used by product designers to assist them in determining the viability of selecting an idea for implementation. The simulation results show that the

Fateme Akbari
Degroote School of Business, McMaster University, Hamilton, Canada
E-mail: akbarif@mcmaster.ca

Morteza Saberi
School of Information, Systems and Modelling, University of Technology Sydney, Australia
E-mail: morteza.saberi@uts.edu.au

Omar K. Hussain (Corresponding author)
School of Business, University of New South Wales (UNSW), Canberra, Australia
E-mail: o.hussain@adfa.edu.au

network structure and the individuals' positions are important factors in the acceptance of an innovation by society. This framework can be used to compare different innovative ideas and provide decision makers in organizations with informative reports as decision support materials.

Keywords Innovation Evaluation · Decision Support System · Product Development · Influence Maximization · Social Network

1 Introduction

In the current proliferated and competitive market, product developers have the challenging task of introducing innovative products that will stand the test of time. They achieve this by utilizing the well-known process of New Product Development (NPD). As shown in Figure 1, the NPD process starts with the step of idea generation, in which ideas to make the product in question innovative are generated, and ends with the step of commercializing, in which the selected innovative ideas are introduced in the market. However, as shown in Figure 1, between these two steps product designers need to do many other steps. Our focus in this paper is on the step of idea screening. The objective of this step is to consider all the generated ideas from the step of idea generation and weed out those ideas from passing to the next steps of NPD, that are not innovative. Among the various decision criteria used by the product designers to achieve the aim of this step, the ability of an idea to make the product innovative is one of them.

However, according to Hagedoorn and Cloodt (2003), innovation is a complicated metric and cannot be measured or judged by a single indicator. Furthermore, with the constant evolution of computing paradigms, the process of evaluating the success of an innovative idea has changed, from being a closed process to an open one. In the closed process, the success of an innovative idea was judged and decided by the product designers themselves. However, with the growth of User-Generated Content (UGC) in social media, this changed in the open process where the opinion of the end users and customers on whom the success of an innovative idea depends on, is taken into consideration by the product designers when deciding about the success of an idea. This is because, in recent years, we have observed the rapid development of social media, which has drastically transformed the way by which people communicate and obtain information. In the business field, consumers increasingly rely on other users' reviews to evaluate products and services prior to making a purchase. Thus, such user-generated content provides an excellent platform for product developers to understand consumer sentiment and visualize relationships between them to pre-determine if an idea will be innovative or not.

True to its importance, the use of user-generated content to evaluate the level of innovativeness of ideas while NPD has attracted much attention Markham et al. (2015); Mirtalaie et al. (2017a); He et al. (2015); Rathore et al. (2016); Jeong et al. (2017); John (2014); Mirtalaie et al. (2017b). However, most of this work focuses on considering the customers' sentiment values which they

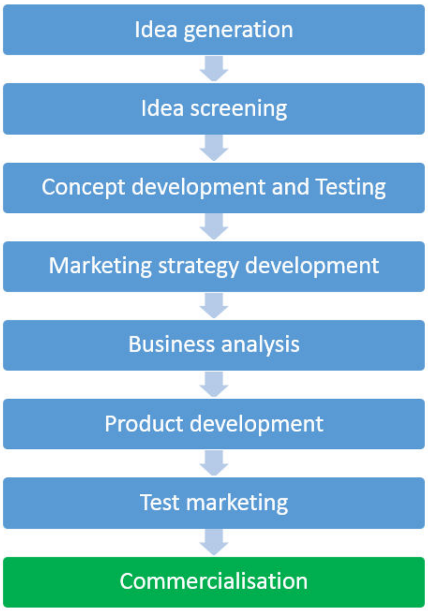


Fig. 1: New product development Process

have expressed towards the ideas in question. Although this provides valuable information to the product designers to judge the feelings of the customers that have expressed their opinion, it does not capture the multitude of other social media customers who have not expressed their opinion, and for whom the product designers are not sure on how will they judge the innovation of a particular idea. However, considering such unknown opinion of the customers' is important because as mentioned in the literature, an individual's decision whether to adopt a product or innovation is extremely dependent on the choices made by its individual peers or neighbors Bharathi et al. (2007). For example, it may be the case that a person whose opinion is known and has a negative opinion may be a very influential person, who will impact other people opinions. So in such case, even if there is only one person with a negative opinion, the product designers should know it to develop appropriate strategies to overcome them.

We address this problem in this paper by making a social network structure of how users are linked in the form of a graph and studying it. In our proposed framework, by using the graph structure we focus on the position of users whose opinion is known and aim to examine the impact of the dissemination of this opinion on the unknown members of the society (graph structure) to achieve a more realistic estimate of their acceptability of the innovation level of the idea in question. It is worth mentioning that the problem of influence and spreading in networks has been widely studied Ballester et al. (2006); Galeotti and Goyal (2009); Kempe et al. (2005); Soma et al. (2014); Shirazipourazad et al. (2012); Wu et al. (2015); Zhang et al. (2016); Tzoumas et al. (2012); Alon et al. (2012); Borodin et al. (2017) but we note a research gap in the literature on using the social network structure and the structural position of members with positive or negative opinion about an idea in measuring the success of an innovation. This will be addressed in this paper whose main contributions are as follows:

- Presenting a novel framework for innovation evaluation with an emphasis on the possibility of opinion cascade.
- Considering the impact of network structure on the acceptability of innovation and the estimation of potential customers' behavior.
- Pay attention to the individuals' position in the network in addition to considering the content of their comments.
- Analyzing the proposed framework using simulation.

The remainder of the paper is organized as follows. Section 2 provides a review of application of sentiment analysis and influence maximization in business. Section 3 proposes a framework for innovation evaluation based on social network. Section 4 describes how a social network can be used to measure and propagate the innovativeness of an idea. Simulation results are presented in section 5 Finally, Conclusions and future research are given in Section 6.

2 Literature review

According to Baregheh et al. (2009) innovation is the multi-stage process whereby organizations transform ideas into new/improved products, service or processes, in order to advance, compete and differentiate themselves successfully in their marketplace. Since implementing innovations burden financial cost on firms, innovation evaluation plays an important role in the success of innovative ideas in companies. Frishammar et al. (2019) believe existing innovation evaluation frameworks neglect some major trends in real world.one of the most important of them is shifting from an analog to a highly digitalized world. Bilgram et al. (2019) focuses on the role and characteristics of lead users in online communities to decrease the risk of innovation acceptance by customers. There are several works with the aim of providing metrics for assessing evaluations in terms of cost, the likelihood of success or competitiveness Rietzschel et al. (2010); Georghiou (1998); Hart et al. (2003); Boly et al. (2014). Bad metrics can lead to poor diagnosis, which in turn results in bad or poorly designed policies with unintended consequences Milbergs and Vonortas (2004). Madzík (2019) considers four criteria to calculate idea priority number. Market share potential is one of the criteria so that the more score an idea get for market share potential, the more chance it get to be successful. Olshavsky and Spreng (1996) is directed toward understanding the process of innovation evaluation by customers to understand this process in order to present an innovative product in a more effective way and thus increase the likelihood that consumers will respond to the innovation favorably.

In order to succeed in a competitive market, innovation must be able to meet the needs of a large part of the users in a distinct way from competitors considering the customers' preferences. Therefore, the importance of customer feedback/review in innovation evaluation is undeniable. Recently, social network analysis has attracted a lot of attention on a variety of topics, including innovation management and new product development in order to convert a large amount of qualitative information into qualitative insights on product features and innovative ideas so that companies can make informed decisions Ireland and Liu (2018). Salehi and Taghiyareh (2014) used multi dimensional opinion cascade to present managerial dashboards improving organizational marketing strategies. A social media competitive analytics framework with sentiment benchmarks is presented in He et al. (2015) a competitive analytical tool for business-driven social media is developed to analyze tweets associated with five major retail companies with the aim of generating meaningful business insight reports. In Hajikhani et al. (2017) user-generated content (UGC) in social network services is analyzed using advanced text analysis techniques. In this work, a comparison between UGC polarities in the sense of being positive and negative is made. They discuss the relationship between UGC polarity in social media and other major innovation ranking indexes. Ozaygen and Balague Ozaygen and Balague (2018) conducted a network analysis based on participants' ideas and comments and found that activities such as presenting ideas, commenting on ideas, and various network centrality degree impact on the positive evaluation received or given by participants. They show that network position criteria of participants are key indicators to analyze idea evaluation process on current crowd innovation contests. Innovation diffusion has been extensively employed to study innovation evaluation. Leite and Teixeira (2012) shows that network size, informational spillovers, and the behavior of innovation prices are important factors in forming the diffusion process. In Kim et al. (2011), a model is presented in which a consumer bases its multi-attribute decision-making on fuzzy TOPSIS and three purchasing forces influence The decision-making process: experts product information provided by mass media, subjective weights on product attributes assigned by individual consumers and social influence. They have demonstrated that the network structure affects the speed of product diffusion. Opinion formation process is considered as a predictive method to anticipate the popularity of different products in social marketplace Salehi and Taghiyareh (2016, 2019). They applied Agent based modelling method and introspective agents to model and simulate opinion formation process in a social marketplace to predict the pattern of user preferences toward different products. Kim and Hur (2013) analyzes the impact of different influence relationship structures existing among individuals. In Pegoretti et al. (2012), the impact of different information regimes on innovation diffusion and competition is taken into account. They differentiate between a perfect information situation, in which customers are perfectly informed about the existence of different innovations and an imperfect information situation, where not all potential customers are informed about innovations availability. Despite these numerous works in the application of social analytics in innovation management and NPD, we notice a gap in existing works that the impact of social structure in innovation evaluation is almost neglected. Considering relationships among individuals and identifying influential people in the network can lead to better innovation management through estimating the cost of spreading positive opinion about an innovation or new product among customers.

Also, there are several works in viral marketing that aim at finding best measures to select a subset of customers for a marketing campaign, in order to achieve a maximum dissemination of messages. If information about the customer network is available, centrality measures provide a structural measure that can be used in decision support systems to select influencers and spread viral marketing campaigns in a customer network Shirazipourazad et al. (2012); Wu et al. (2015); Zhang et al. (2016); Wu et al. (2013); Kiss and Bichler (2008); Kratzer et al. (2016). In recent years, we have observed the rapid development of social media, which has drastically transformed the way in which people communicate and obtain information. Currently, social media has become ubiquitous and plays an increasingly critical role in today's business environments. A number of companies use social media tools such as Facebook and Twitter to provide a variety of services and to interact with customers. As a result, a large amount of user-generated content is available on social media sites. User-generated content offers opportunities and challenges to businesses. In the business field, consumers increasingly rely on user-generated reviews to evaluate products and services prior to making a purchase. Thus, companies are expected to harness this user-generated data to extract entities and themes, to understand consumer sentiment, to visualize relationships and to create their marketing intelligence to excel in the business environment. In particular, organizations can benefit from User-generated content analysis to become aware of customers' opinion about their products and innovative ideas. Advanced data analytics is one of the most revolutionary technological developments in the 21st century, which enables us to discover underlining trends via sophisticated computational methods. On various e-commerce and social platforms, millions of online product reviews are published by customers, which can potentially provide designers with invaluable insights into product design.

Despite the importance of social network structure, there is a research gap on the impact of social network structure and the structural position of members with positive or negative opinion about an innovation in the success or failure of an innovation. In our proposed framework, we focus on the importance of the graph structure and position of individuals with the aim of examining their impact on the dissemination of opinion in society in order to achieve a more realistic estimate of the acceptability of innovation in the customer network.

3 Proposed framework

In the current business world, social media plays a major role in shaping the opinions of people in society. Social networks as a means of expressing opinions of individuals contains a wide range of information about the views of people in society around various issues. So gathering and reviewing these user generated contents will play a significant role in determining the marketing strategies. Our proposed framework for evaluating the innovativeness of ideas by using social network structure consists of four components as shown in Figure 2.

The first component is data collection that collates the data required for fur-

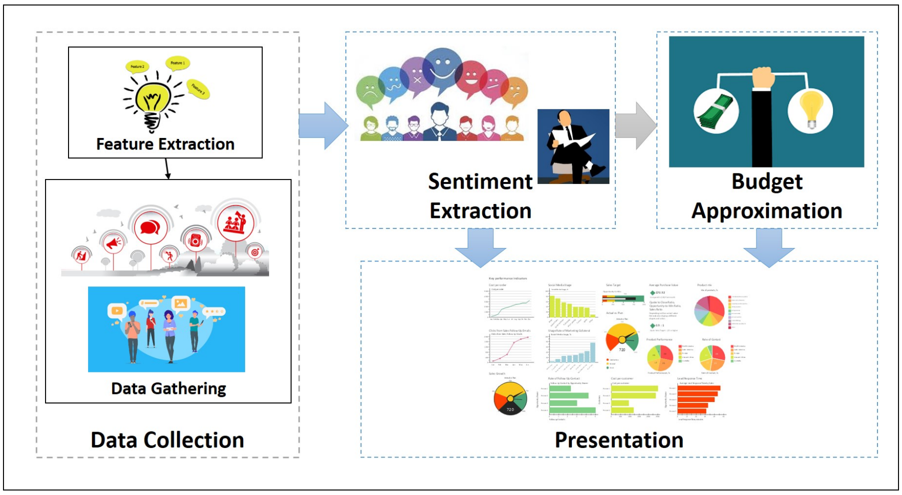


Fig. 2: The proposed framework for innovation evaluation through information propagation in a social network

ther analysis in the next components. The data collation is done at two levels, namely feature extraction and feature data gathering. At feature extraction level, the objective is to identify which existing features are close representative to the idea whose innovativeness is being evaluated. Such identified features form the basis in the feature gathering level, for gathering relevant information from the potential customer community. For example, let us suppose we want to examine the innovativeness of using face recognition in a gadget. This can be done by first extracting the relevant features of that idea (face recognition) and then either holding a campaign to have explicit opinion of customers on that idea or capturing customers' comments from social network about that idea in products with similar features, such as the mobile phones, and reviewing them.

This leads to the second component of the framework, namely sentiment extraction. In real world scenarios, not every person expresses his/her opinions about an issue. So, from the customers' community (formed social network structure) used in feature data gathering task, we may have a group of customers who have expressed their opinion while another group have not. However, as our objective is to make a good representation of what customers think about the innovativeness of our idea, we need to know the opinion of the whole customer community. For this, we divide the customers' community into two parts; namely known and unknown. Known represents those customers' who have expressed either their +ve or -ve opinion towards the idea whereas unknown represents those customers who have not expressed their opinion. +ve refers to positive atitude of customer towards an idea so that make him adopt it while -ve represents negative attitude. The objective in this component is to determine the sentiment of the opinion expressed by the known customers (nodes of the social network structure) and then use it as a basis to determine the level of innovation of the whole customer community towards an idea. This is by considering the connection between the known and unknown users.

This will be done in the third component of the framework, namely budget approximation. Our objective in this component is to estimate the cost of propagating the positiveness about an idea among the unknown customers by using the sentiment of the known customers. We do that by defining budget as the metric, which determines the number of customers (nodes) from the unknown group whose opinion needs to change to make the overall opinion of community towards an innovation idea as positive as they need. In other words, this component for an idea approximates the budget needed to impress the nodes which are representation of whole community beyond a certain threshold, to ensure that it is accepted by the customers when introduced. This analysis is utilized in the fourth and last component for decision-making.

The fourth component of the framework is presentation in which the analysis of the previous components is used for decision-making. In this component, a report will be generated which provides decision makers (product designers) with comparative information on the various potential innovation ideas being analyzed. The top ranked ones can be selected further for implementation by the product designers depending on how much resources they can invest. In our previous work, we have developed approaches that assist product designers in the data collection and feature extraction phases Mirtalaie et al. (2018, 2017a,b). Our focus in this paper is on the third component of the framework, namely budget approximation. As discussed earlier, the objective of product designers in this component is to assess two aspects. The first is to assess the position of users whose opinion is known and aim to achieve a realistic estimate of their acceptability of the innovation level of the idea in question. Based on that, the second is to determine how much of effort do the product designers need to invest to change the opinion on the unknown members of the society (graph structure) if they want to increase the innovativeness of an idea. We explain that further in the next section.

4 Using social networks to assess and propagate the innovativeness of an idea

To explain our proposed approach of how social networks can be used to determine the innovativeness of an idea and propagate it further among nodes whose opinion is unknown, let us consider the social network structure as shown in Figure 3a. From this figure, we see that node A, which is a known customer with a positive opinion is connected to other nodes of the network, whose opinion is neutral or non-negative at this stage. So, in the current state, the level of innovativeness of an idea being evaluated is very low, as only one node out of the fourteen is known to be as positive.

To measure the second aspect of how much of an effort does the product designers have to make to propagate the innovativeness of an idea further in the network, we assume that for each unknown node if a pre-specified portion (in this case, 50%) of its neighbors are positive to an opinion, then that node accepts that opinion too. So, when node A is positive towards an opinion and becomes active (which refers to a node who has positive opinion about the idea), then among its neighbors (B, E, F, G, I, J, K, H), in the first step only four nodes (E, F, G, I) as shown in Figure 3b, will be affected by the opinion of node A. This is because at least 50% of neighbors of these nodes are active. For example, F and I have two neighbors which among them, one (A) is active and E and I have just one neighbor, A which is active. But for nodes B, J, K and H, less than 50% of nodes are active, so these nodes will not become active at this step. In the second step, there are five active nodes; A, E, F, G, I, and these nodes will affect their neighbors B and J to become active, as shown in Figure 3c. The opinion of other nodes will not change because less than 50% of their neighbors are active. This will change in the next step, as shown in Figure 3d where nodes C, D, K will become active. In the next step, node H will become active as shown in Figure 3e and in the next step, nodes L, M will become active as shown in Figure 3f. Finally, in the last step, node N will become active as shown in Figure 3g.

Using such an approach, the product designers can determine not only how much of effort they need to propagate the innovativeness of an idea among the unknown nodes but also the influential node of the network to start the process from. The above analysis shown in Figure 3 is based on starting the process from node A. Let us suppose that instead of node A, node I is activated at the initial stage. This will not result in any change in the opinion of other nodes. However, in the case of selecting node D, only node C will change his/her opinion. This demonstrates the importance of determining the inferentiality of the starting node and its role in propagating the innovativeness of an idea among unknown nodes. For example, with a slight change in the structure of the network by adding two links ($E-C$ and $B-I$) from Figure 3a as shown in Figure 4, node A is not as influential as how it was in Figures 3a to 3g. In other words, it can only influence nodes F and G of the network from the fourteen available nodes. Therefore, apart from the structural position of each node in the network the overall structure of the network too plays an important role

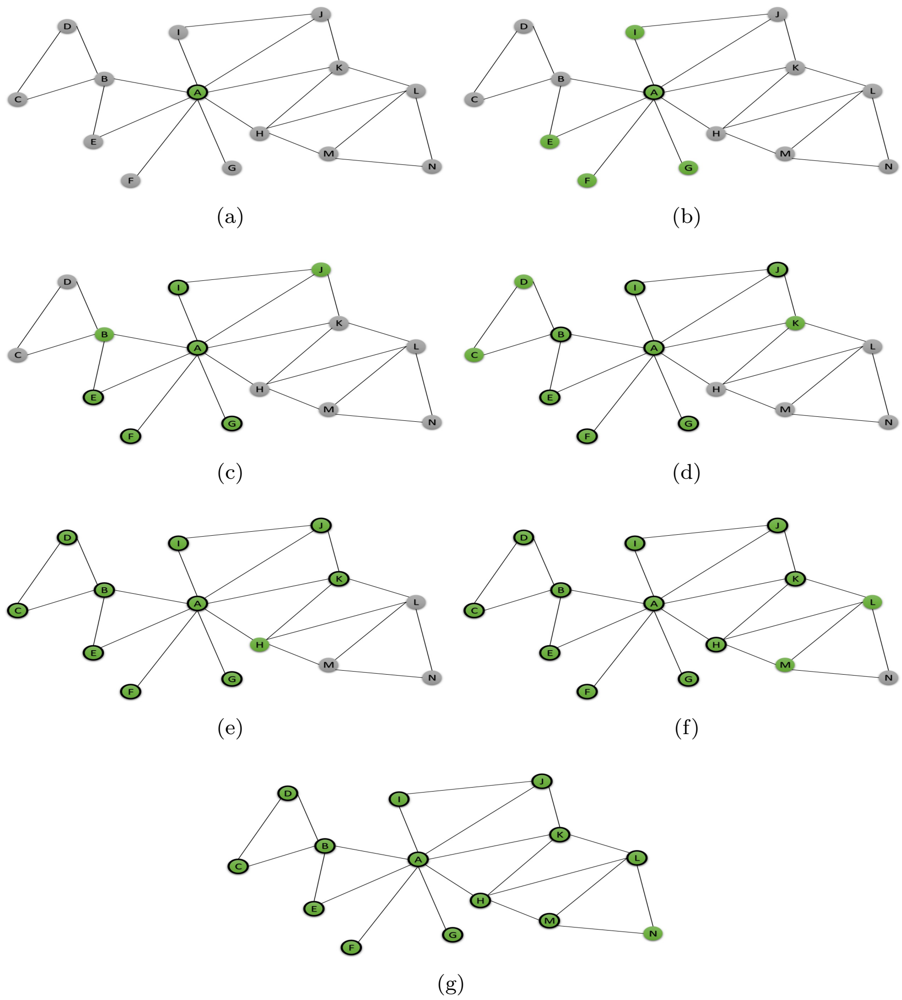


Fig. 3: The process of opinion diffusion among nodes of a social network

in opinion diffusion.

Despite the importance of social network structure, there is a research gap on the impact of social network structure and the structural position of members with positive or negative opinion about an innovation in the success or failure of an innovation. In our proposed framework, we address that by focusing on the importance of the graph structure and position of individuals with the aim of examining their impact on the dissemination of opinion in society in order to achieve a more realistic estimate of the acceptability of innovation in the customer network.

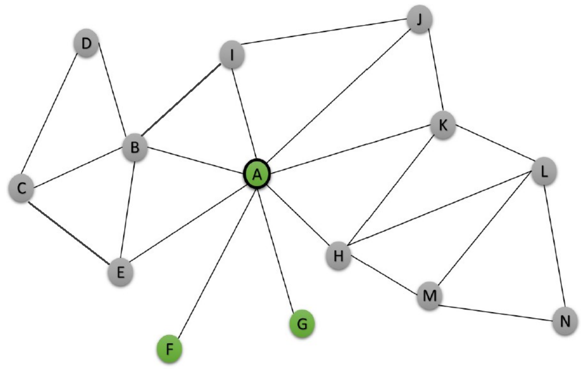


Fig. 4: The effect of network structure change in opinion diffusion

5 Using social network to propagate the innovativeness of ideas

In this section, we present by using simulation how social network can be used by product designers to determine and propagate innovativeness of ideas while developing new product. For basing the results on real-world data, we exploit the Amazon book review dataset He and McAuley (2016) and assume that each book in that review represents an innovative idea. We extract 23 ideas in this step. In the second component of the framework, we analyze the relevant reviews on each book and use the method presented in Socher et al. (2013) to identify the sentiment associated with each review. For sentiment analysis a Treebank which consists information about the sentiment of phrases is used. For each sentence, the Treebank as shown in Figure 5 is constructed by extracting its phrases and determining the sentiment of each of them.

The sentiment of each phrase in the treebank is determined by using Recursive Neural Tensor Network (RNTN). This method receives a sentence as an input and by forming a binary tree of the words and phrases in the text, extracts the sentiment of phrases. Subsequently, it proceeds recursively on different levels of the word tree to extract the sentiment of the entire sentence. The sentiment of each phrase is determined over five levels, namely very negative, negative, neutral, positive and very positive. However, in our approach we do not consider the severity of the opinion. In other words, the polarity of negative and very negative are considered as -1, neutral is considered as 0, and positive and very positive are considered as +1. Figure 5 shows the tree of a sample review statement.

The next task is to generate the social network that represents the customers in whom the company wants to test the popularity of the idea. As the social

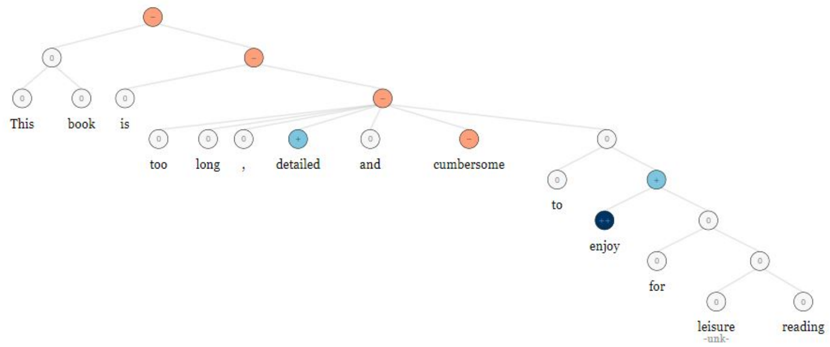


Fig. 5: Tree of a sample review

Table 1: Structural features of generated networks

Feature	Scale Free	Complete graph	Random graph	WattsStrogatz
number of nodes	1000	1000	1000	1000
Average Degree	10	249	10	10
Density	0.01	1	0.01	0.01
Clustering Coefficient	0.0606	1	0.0102	0.717

network of individuals is not presented in dataset, we need to generate this graph synthetically and then assign extracted sentiments for each idea from previous stage to different individuals in order to simulate different potential cases in real world. To construct the social network of individuals, in our simulation we use four different types of graphs; namely complete graph in which all nodes know each other, random graph in which links between nodes are generated randomly Bollobás (2001), WattsStrogatz network in which each node generate a certain number of links to the next nodes and rewire the existing links with a predefined probability Watts and Strogatz (1998), and scale free network whose degree distribution follows the power law R and Albert-Lszl (2002). Some structural features of generated graphs are presented in Table 1.
As we have a real data set of customer's reviews which is used as the opinion of customers but we do not know their social relations, we need to assign the extracted sentiments to nodes in different types of graphs. For assigning the sentiment of ideas to the nodes (or individuals) we used three methods, namely random method, MaxMin and MinMax. In MaxMin method, positive sentiments, extracted in previous step, are assigned to nodes that have the highest degree and negative extracted sentiments are assigned to nodes with the lowest degree. Similarly, in MinMax method, positive sentiments are assigned to nodes that have the lowest degree whereas negative sentiments are assigned to nodes with the highest degree. In random method we assign sentiments to nodes randomly. The pseudo-code for assigning the nodes with the sentiment is presented in Figure 6. Nodes with no assigned sentiment are considered as

```
INPUT: reviews ({R_1, R_2, ..., R_r}), reviewers id, social network structure ( G(V,E) ), marketing budget
(budget), assignment method ({M_1, M_2, ..., M_m})
OUTPUT: sentiment of each review, final state of graph after opinion diffusion for each budget
FOR i = 1 ... r DO:
    sentiment <- RNTN(R_i);
    SentimentFile <- write(sentiment, reviewer id);
END FOR
FOR i = 1 ... m DO:
    assign sentiment to reviewers in social network based on method M_i
    Cascade positive and negative opinions based on LTM
    FOR b = 1 ... budget DO:
        Based on LTM and a greedy method Select b individuals whose positive opinion have
        maximum effect on social network
        Calculate agents with positive opinion (P), negative opinion (N) and neutral (L)
        BudgetFile <- write(M_i, b, P, N, L)
      IF L = 0 THEN
          Break
      END IF
    END FOR
END FOR
```

Fig. 6: The pseudo-code for assigning sentiment value to the nodes

those having a neutral sentiment. The number of nodes considered in the social network structure is 1000. Figure 7 shows the initial distribution of positive and negative sentiment for the 23 innovative ideas among 1000 individuals. A decision based on this distribution leads in selecting innovative idea 12 as it has the highest level of positive opinions for it. However, this decision output does not consider the important point that for most other ideas, a large portion of community is neutral, so there is a strong potential to impress them by using opinion propagation.

Linear threshold model(LTM) Mark (1978) is used for opinion propagation or influence maximization. This model describes the process of diffusion of an opinion in the society. In this model, nodes are connected to each other with weighted links. The sum of input links' weights equals to 1 for each node. A node is said to be active when it is exposed to an opinion and accepts it, and it is said to be inactive when it is not exposed to an opinion or rejects it. An inactive node becomes active if it receives and accepts the message. Also, a threshold(θ) is defined for each node. In each step, if the total weight of the

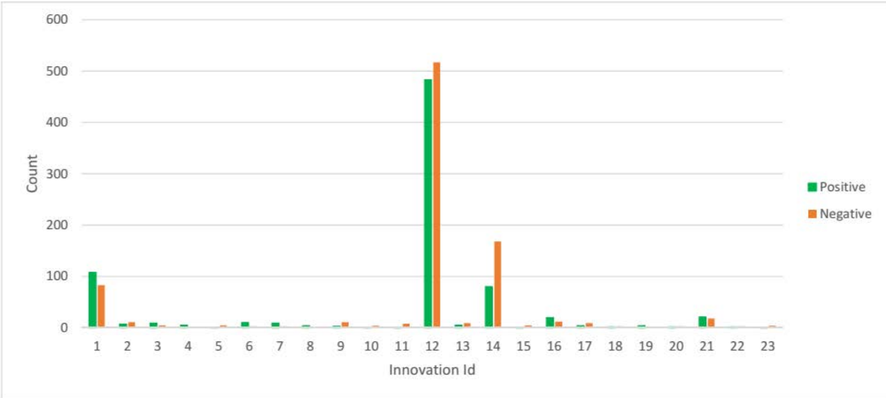


Fig. 7: The number of individuals with non-neutral (positive /negative) opinions about different innovative ideas

input links from the active neighbors of a node is greater than the defined threshold, the node will be activated. For example, in Figure 8, we have a social network with four nodes and three links between them, v_2 and v_4 are active at the time instant t. At time t + 1, the node v1 will be activated because $w(v_1, v_2) + w(v_1, v_4) \geq \theta_{v_1}$. We use LTM for modeling the distribution on the network, we try to find the minimum number of people who can maximize the impact on the network. In our simulation activation threshold for all nodes equals to 0.5 and the weight of each incoming link to node i equals to $1/L_i$, where L_i is the number of incoming links for node i.

Figure 9 illustrates the number of nodes that have accepted innovation 1 according to the influence propagation/maximization strategy used. The horizontal axis shows the budget which is used for influence maximization and the vertical axis shows the number of nodes that have accepted innovation 1. As mentioned before, we have extracted the opinion sentiment of people, but we have no information about the structural position of people in the community. Structural position of nodes is important in opinion propagation because it can affect the amount of influence that they might have on other people in the community. Thus, we applied three methods for assigning extracted sentiments to nodes in the network; MinMax, MaxMin and Random. Using these three different methods results in assigning positive, negative or neutral opinion to people with different positions in the community. Now, we want to analyze the effect of structural position on the budget needed to spread opinion throughout the communities with different relational topology.

Figure 9a shows this information for the case when the social network is a complete graph. In this figure, all three methods of initial assignment act the same because the threshold for activating a node is 0.5 and in a complete graph each node has $n-1$ links, so half of the nodes must be activated so that the propagation occurs. Therefore, in each step only the node which is activated

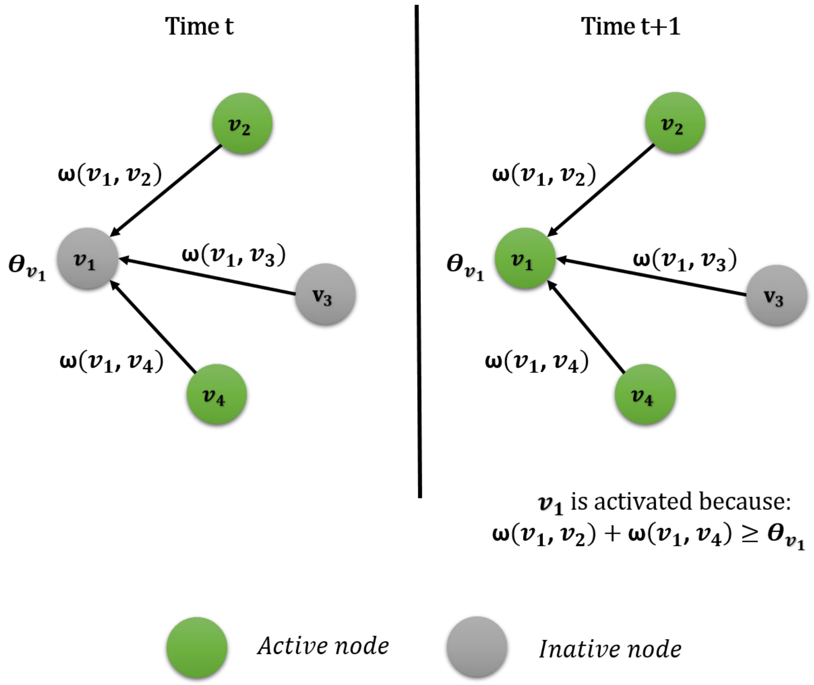
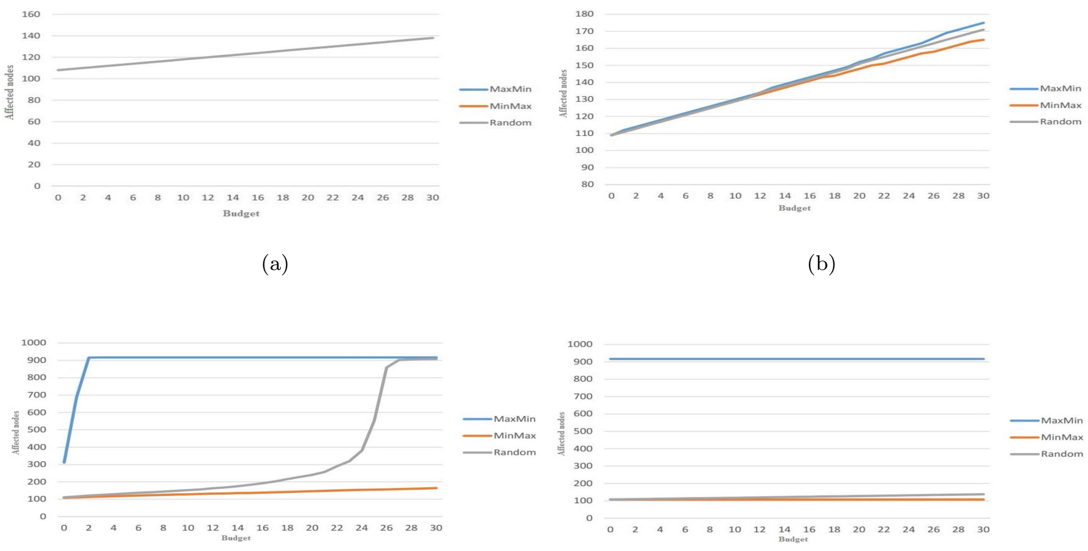


Fig. 8: Node activation in Linear Threshold Model

by influence maximization budget is added to active nodes. Figure 9b shows the information for the case when the social network is a random graph. In this figure, all three methods of initial assignment act almost the same because links are generated randomly and node degrees are almost similar. However, the difference between structural position of nodes, which are selected for initial opinion assignment, resulted in minor difference in the number of affected nodes. Figure 9c shows this information for the case when the social network is a scale free graph. As the degree distribution follows power law, there exists a few nodes with a high degree, named hub. These nodes usually play a critical role in opinion propagation. In this figure, there are distinct differences in the budget needed for opinion diffusion throughout the network. In MaxMin method, the hubs are being activated first, so the opinion is propagated among more than 90% of individuals using only two units of budget. When random method is used, more budget is needed for propagation throughout the network. In Min- Max method, the negative opinions are assigned to the hubs, so the opinion is propagated among network slowly. Figure 9d shows this information for the case that the social network is a Watts-Strogats graph. In this graph, we assume that there are n nodes and each node is assigned with an id from 1 to n. there are two parameters; D for nodal degree and P for rewiring probability for each link.

In the Watts-Strogats graph, each node generates a link to the D next nodes



(a) (b)

(c) (d)

Fig. 9: Opinion diffusion using different assignment methods in (a) complete graph, (b) random graph, (c) scale free graph and (d) Watts-Strogatz graph

and the last nodes generate links to the first nodes in a cyclic manner, so the outgoing degree of all nodes is the same. Using MaxMin assignment method, 1 is assigned to the m first nodes (1 to m) in the graph and -1 is assigned to the k last nodes ($n-k$ to n), where m is the number of positive sentiments and k is the number of negative ones. As in the simulation only the opinion of neutral nodes can change, the first nodes' opinion remains unchanged, and the propagation of negative sentiment stops because nodes with negative sentiment mostly have links to nodes with positive sentiment and cannot change their opinion. For positive nodes, next D nodes are mostly neutral and the propagation of positive opinion is probable. Using MinMax method everything is reversed. It is noteworthy that, although the outgoing degree of all nodes is similar, the position of nodes with positive and negative opinion and the distance between them in a graph can influence the opinion diffusion. Figure 9 illustrates that the position of nodes with different opinion can affect the final opinion of the community.

Figure 10 shows that even by using the same method for assigning opinions to nodes, the network structure can influence the way in which an opinion is propagated in the society. In each of the graphs of Figure 10, we can see that using any method of assigning opinions, networks with different structures display different behaviors in such a way that it is impossible to establish a specific ranking for the preference of the network structures or certain rules for decision making. Therefore, the dissemination of opinion and its impact on the whole society in each case require a comprehensive and complete examination.

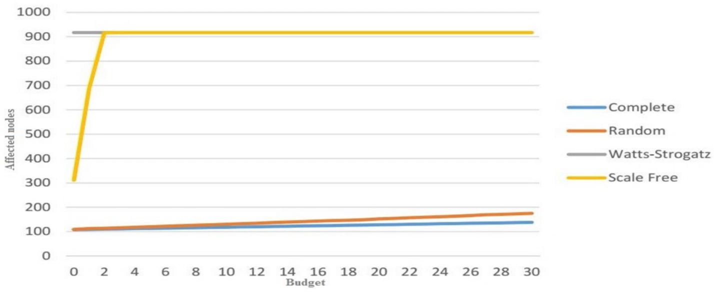
Regarding the graphs presented in Figure 9 and 10, it can be clearly seen that the network structure and the position of each individual in the network can influence the overall opinion of the community. Therefore, giving attention only to customer reviews, regardless of the network structure and the position of the reviewer in the network, can lead to inappropriate decisions. In this simulation, we assumed that for each innovation, 30 units of budget are allocated. For each innovation, we try to make the most impact on the network with the lowest possible budget so that the highest number of people have positive opinion about the innovation. In fact, the goal is to investigate the amount of budget needed to make the most impact on the society. This budget is considered as the innovation cost. In order to compare innovations, it should be examined how much of money is required to affect the community so that the most possible number of customers have positive opinion. The maximum budget is 30. Thus, the simulation stops in two cases; first, when there is no other neutral node to change his/her opinion, that is, all nodes opinions are 1 or -1. Second, when the marketing budget is over.

Figure 11 shows the final opinion of the society at the end of the simulation considering opinion propagation. This figure shows the information for the case when the initial distribution of opinion is random. Figure 11a shows the information when the social network structure represents a complete graph, Figure 11b shows it for a random graph, Figure 11c shows it for a Watts-Strogatz graph and Figure 11d shows it for a scale free graph.

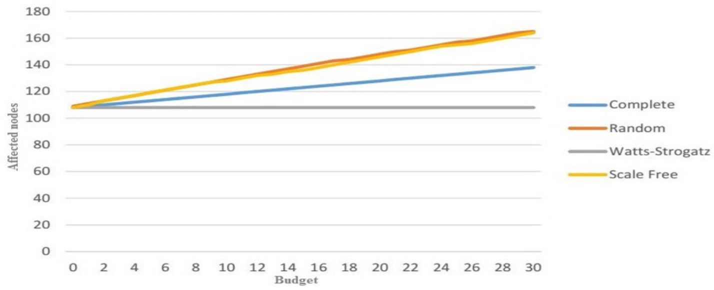
From the figure, it can be seen that for complete and random graphs, the best possible idea is the same (Innovation idea 12) as Figure 7. This innovation with a budget of zero influences nearly 50% of the community. In the Watts-Strogatz graph, innovations 7, 8 and 11 affects almost all of the community but innovation 11 uses the least budget. Also, innovation 14 too is worth exploring. Innovation 1 in the scale free graph has good conditions. This innovation, even though uses the total budget, has been able to affect the entire community. Thus, by using such analysis, product designers can make informed decisions of which innovative idea should they choose and why.

6 Conclusion

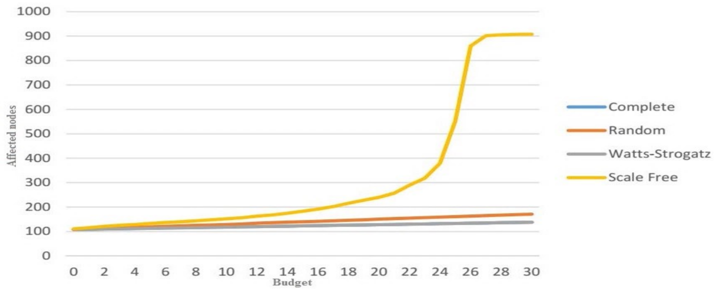
In this paper, a framework for innovation evaluation is presented that considers the social structure of customer network. The proposed framework consists of four major components; a component for data collection, a component for extracting the sentiment of customers, a budget approximation component and the presentation component. First, in data collection phase, data is gathered considering related features to the innovations and it is used to analyze sentiment of customers. Then, the budget needed for spreading the positive opinion about the innovation is estimated, and finally generated informative reports



(a)

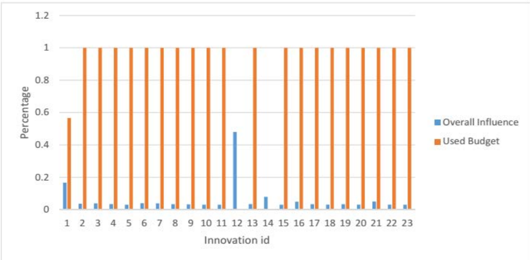


(b)

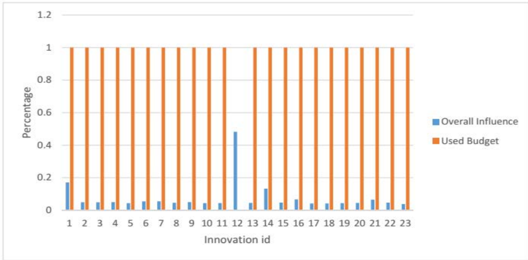


(c)

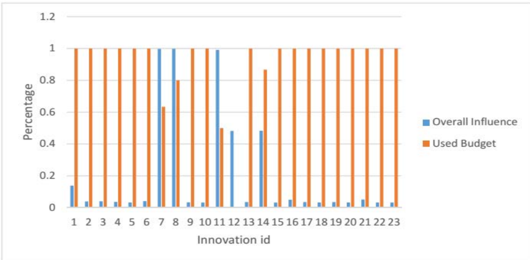
Fig. 10: Opinion diffusion in different graph structure applying (a) MaxMin, (b) MinMax and (c) Random method



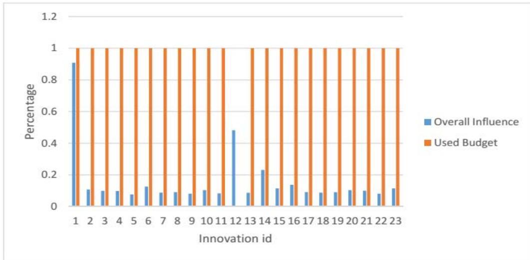
(a)



(b)



(c)



(d)

Fig. 11: The overall influence and used budget for each innovation in (a) complete graph, (b) random graph, (c) Watts-Strogatz graph and (d) scale free graph

will be presented to decision makers. The proposed framework has been simulated using Amazon dataset, and results confirm the importance of taking the network structure into account in making a decision about implementing an innovation prior to product development. While novel, the proposed approach has directions of future work in which it can be improved further. In this work, we assumed that the network is known while in several areas the network is partially known, so the relation between nodes should be predicted to create a graph closer to the real one. Although we assumed that the cost of changing opinion for all nodes is the same, in reality, the cost of changing people's opinions varies. Moreover, the probability of unsuccessful attempts to change the opinion of individuals should be considered. In our framework, we only focused on positive opinion while in real world people may have negative opinion toward a product or an idea. modeling the effect of negative opinion can be considered to improve proposed mehod For the simplicity of the model we assumed that all nodes have the same threshold of acceptance while users are heterogeneous and have different acceptance thresholds that vary from one to another and may also be affected depending on the type of product or idea that is spreading in the network. Also, innovation evaluation in the presence of other competitors is a challenging issue that could be considered. Another aspect that can be considered is the allocation of variable budget to different ideas. Also applicability of the proposed framework in other applications like political and organizational area can be investigated.

References

Alon N, Gamzu I, Tennenholtz M (2012) Optimizing budget allocation among channels and influencers. In: Proceedings of the 21st international conference on World Wide Web, ACM, pp 381–388

Ballester C, Calvó-Armengol A, Zenou Y (2006) Who's who in networks. wanted: The key player. Econometrica 74(5):1403–1417

Baregheh A, Rowley J, Sambrook S (2009) Towards a multidisciplinary definition of innovation. Management decision 47(8):1323–1339

Bharathi S, Kempe D, Salek M (2007) Competitive influence maximization in social networks. In: International Workshop on Web and Internet Economics, Springer, pp 306–311

Bilgram V, Brem A, Voigt KI, et al. (2019) User-centric innovations in new product developmentsystematic identification of lead users harnessing interactive and collaborative online-tools. Managing Innovation: Understanding And Motivating Crowds 32:173

Bollobás B (2001) Random graphs. 2nd edit

Boly V, Morel L, Camargo M, et al. (2014) Evaluating innovative processes in french firms: Methodological proposition for firm innovation capacity evaluation. Research Policy 43(3):608–622

Borodin A, Braverman M, Lucier B, Oren J (2017) Strategyproof mechanisms for competitive influence in networks. Algorithmica 78(2):425–452

Frishammar J, Richtnér A, Brattström A, Magnusson M, Björk J (2019) Opportunities and challenges in the new innovation landscape: Implications for innovation auditing and innovation management. European Management Journal 37(2):151–164

Galeotti A, Goyal S (2009) Influencing the influencers: a theory of strategic diffusion. The RAND Journal of Economics 40(3):509–532

Georghiou L (1998) Issues in the evaluation of innovation and technology policy. evaluation 4(1):37–51

Hagedoorn J, Cloodt M (2003) Measuring innovative performance: is there an advantage in using multiple indicators? Research policy 32(8):1365–1379

Hajikhani A, Porras J, Melkas H (2017) Brand analysis in social network services: Results from content analysis in twitter regarding the us smartphone market. International Journal of Innovation and Technology Management 14(02):1740008

Hart S, Jan Hultink E, Tzokas N, Commandeur HR (2003) Industrial companies' evaluation criteria in new product development gates. Journal of Product Innovation Management 20(1):22–36

He R, McAuley J (2016) Ups and downs: Modeling the visual evolution of fashion trends with one-class collaborative filtering pp 507–517

He W, Wu H, Yan G, Akula V, Shen J (2015) A novel social media competitive analytics framework with sentiment benchmarks. Information & Management 52(7):801–812

Ireland R, Liu A (2018) Application of data analytics for product design: Sentiment analysis of online product reviews. CIRP Journal of Manufacturing Science and Technology

Jeong B, Yoon J, Lee JM (2017) Social media mining for product planning: A product opportunity mining approach based on topic modeling and sentiment analysis. International Journal of Information Management

John F (2014) Social media and innovation: The relationship between firms facebook activity and product innovation development. Master's thesis, University of Twente

Kempe D, Kleinberg J, Tardos É (2005) Influential nodes in a diffusion model for social networks. In: International Colloquium on Automata, Languages, and Programming, Springer, pp 1127–1138

Kim J, Hur W (2013) Diffusion of competing innovations in influence networks. Journal of Economic Interaction and Coordination 8(1):109–124

Kim S, Lee K, Cho JK, Kim CO (2011) Agent-based diffusion model for an automobile market with fuzzy topsis-based product adoption process. Expert Systems with Applications 38(6):7270–7276

Kiss C, Bichler M (2008) Identification of influencersmeasuring influence in customer networks. Decision Support Systems 46(1):233–253

Kratzer J, Lettl C, Franke N, Gloor PA (2016) The social network position of lead users. Journal of Product Innovation Management 33(2):201–216

Leite R, Teixeira AA (2012) Innovation diffusion with heterogeneous networked agents: a computational model. Journal of Economic Interaction and Coordination 7(2):125–144

Madzík P (2019) Capture and evaluation of innovative ideas in early stages of product development. The TQM Journal

Mark G (1978) Threshold models of collective behavior. American journal of sociology 83(6):1420–1443

Markham SK, Kowolenko M, Michaelis TL (2015) Unstructured text analytics to support new product development decisions. Research-Technology Management 58(2):30–39

Milbergs E, Vonortas N (2004) Innovation metrics: measurement to insight. Center for Accelerating Innovation and George Washington University, National Innovation Initiative 21st Century Working Group 22

Mirtalaie MA, Hussain OK, Chang E, Hussain FK (2017a) A decision support framework for identifying novel ideas in new product development from cross-domain analysis. Information Systems 69:59–80

Mirtalaie MA, Hussain OK, Chang E, Hussain FK (2017b) Sentiment analysis of specific products features using product tree for application in new product development. In: International Conference on Intelligent Networking and Collaborative Systems, Springer, pp 82–95

Mirtalaie MA, Hussain OK, Chang E, Hussain FK (2018) Extracting sentiment knowledge from pros/cons product reviews: Discovering features along with the polarity strength of their associated opinions. Expert Systems with Applications 114:267–288

Olshavsky RW, Spreng RA (1996) An exploratory study of the innovation evaluation process. Journal of Product Innovation Management: AN INTERNATIONAL PUBLICATION OF THE PRODUCT DEVELOPMENT & MANAGEMENT ASSOCIATION 13(6):512–529

Ozaygen A, Balague C (2018) Idea evaluation in innovation contest platforms: A network perspective. Decision Support Systems 112:15–22

Pegoretti G, Rentocchini F, Marzetti GV (2012) An agent-based model of innovation diffusion: network structure and coexistence under different information regimes. Journal of Economic Interaction and Coordination 7(2):145–165

R A, Albert-Lszl B (2002) Statistical mechanics of complex networks. Reviews of modern physics 74(1):47

Rathore AK, Ilavarasan PV, Dwivedi YK (2016) Social media content and product co-creation: an emerging paradigm. Journal of Enterprise Information Management 29(1):7–18

Rietzschel EF, Nijstad BA, Stroebe W (2010) The selection of creative ideas after individual idea generation: Choosing between creativity and impact. British journal of psychology 101(1):47–68

Salehi S, Taghiyareh F (2014) Decision making improvement in social marketing strategy through dependent multi-dimensional opinion formation. In: 2014 4th International Conference on Computer and Knowledge Engineering (ICCKE), IEEE, pp 111–116

Salehi S, Taghiyareh F (2016) Introducing a more realistic model for opinion formation considering instability in social structure. International Journal of Modern Physics C 27(11):1650136

Salehi S, Taghiyareh F (2019) Introspective agents in opinion formation modeling to predict social market. In: 2019 5th International Conference on Web Research (ICWR), IEEE, pp 28–34

Shirazipourazad S, Bogard B, Vachhani H, Sen A, Horn P (2012) Influence propagation in adversarial setting: how to defeat competition with least amount of investment. In: Proceedings of the 21st ACM international conference on Information and knowledge management, ACM, pp 585–594

Socher R, Perelygin A, Wu J, Chuang J, Manning CD, Ng A, Potts C (2013) Recursive deep models for semantic compositionality over a sentiment treebank pp 1631–1642

Soma T, Kakimura N, Inaba K, Kawarabayashi Ki (2014) Optimal budget allocation: Theoretical guarantee and efficient algorithm. In: International Conference on Machine Learning, pp 351–359

Tzoumas V, Amanatidis C, Markakis E (2012) A game-theoretic analysis of a competitive diffusion process over social networks. In: International Workshop on Internet and Network Economics, Springer, pp 1–14

Watts DJ, Strogatz SH (1998) Collective dynamics of small-world networks. nature 393(6684):440

Wu H, Liu W, Yue K, Huang W, Yang K (2015) Maximizing the spread of competitive influence in a social network oriented to viral marketing. In: International Conference on Web-Age Information Management, Springer, pp 516–519

Wu J, Hu B, Zhang Y (2013) Maximizing the performance of advertisements diffusion: A simulation study of the dynamics of viral advertising in social networks. Simulation 89(8):921–934

Zhang J, Wang S, Zhan Q, Yu PS (2016) Intertwined viral marketing in social networks. In: Proceedings of the 2016 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining, IEEE Press, pp 239–246