

Capturing influential people: effective public relations activities on Instagram

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Abstract

This study aims to clarify how small and medium-sized enterprises (SMEs) can effectively utilise social media to increase their number of followers, with a focus on raising awareness of their company name and products. Specifically, we will examine the Instagram-based publicity activities of Company I, an agricultural machinery manufacturer located in the Tohoku region of Japan, which has not previously engaged in social media-based publicity activities. The authors aim to clarify how the structure of followers is formed from this starting point.

JEL classification: L60, L63, M14

Keywords: talent, global, management, cross-border, Japan, innovation, transformation

1. Overview

For small and medium-sized enterprises in rural areas, labour shortages are a serious problem, and the COVID-19 pandemic has led to an increase in marketing efforts using Instagram. Generally, small and medium-sized agricultural machinery manufacturers in Japan often supply products to large agricultural machinery manufacturers on an OEM basis and entrust them with sales. These large manufacturers then sell the products through agricultural cooperatives composed of farmers at trade shows. However, some small businesses have also sold their products through agricultural cooperatives and provided delivery and after-sales service.

As the aging of farmers progresses and more farms go out of business, there is also an increase in young people from completely unrelated fields entering the agricultural industry. This means that more farmers are choosing not to join agricultural cooperatives, making it increasingly difficult to rely solely on sales through traditional cooperatives. Agricultural machinery can now be purchased online. In such agricultural machinery industry, it is extremely important to research marketing strategies that utilise social media.

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2. Experimental Subjects and Analysis Methods

2.1 Survey Target Company

The survey target company, Company I, is an agricultural machinery manufacturer with over 100 years of history. It is a small-to-medium-sized enterprise located in the Tohoku region of Japan with approximately 60 employees. From this number of employees, five are sales representatives who primarily conduct sales activities in the Tohoku region and the Tokai and Kansai regions (300–700 km from the head office). Its main products include rice transplanting machines and seedling cultivation machines. Due to the COVID-19 pandemic and resulting travel restrictions, the company explored alternative sales methods. Initially, they implemented measures using a TV conferencing system, but this proved ineffective as the majority of customers were individual farmers in rural areas, many of whom were elderly. As a result, the company felt the need to enhance the recognition of its brand name and products.

Instagram is a relatively late entrant in the social media space and was acquired by Meta. While similar to Facebook, it is a photo-centric social media platform, making it easier to showcase products and relatively accessible for data collection, which is why it was selected. Company I has been using YouTube to demonstrate the assembly and usage of agricultural machinery since 2017. Regarding Facebook, the company initially used it under the CEO's personal account from 2019 for four years and began using it under the company name for public relations in 2022. This study focuses solely on Instagram for analysis, and no integration with other social media platforms was conducted during the data collection period.

2.2 Analysis Methods

2.2.1 Data Sources and Visualisation

In this study, we obtained user IDs using the Instagram API. We identified the users' locations based on their self-introductions. We used “follower data” showing the follow/follower relationships between users who directly follow I Company's Instagram account (hereinafter referred to as “direct followers”) as the data source. We created a network diagram based on this data. This network diagram visualises the follow-follower relationships as a graph, where ‘users’ are nodes and ‘follow-follower relationships’ are edges. Hereinafter, this graph will be referred to as the ‘follower network.’

2.2.2 Evaluation indicators: Influencer index and ‘like’ rate

In this study, in order to extract high-quality influencers from among followers, we defined ‘users with 1,000 or more followers.’ The influencer index is expressed by the following formula 1.

$$\text{Influencer index} = \left\{ \left(\frac{\text{Number of 'likes' + number of comments}}{\text{Number of followers}} \right) \div \text{Number of posts} \right\} + \frac{\text{Number of followers}}{\text{Number of followings}} \cdot \cdot \cdot \text{Formula 1}$$

Equation 2 is used by Tafesse and Wood (2021) and many other marketing studies to calculate the ‘engagement rate’ on Instagram, and we will use it in this study as well.

$$\left\{ \left(\frac{\text{Number of 'likes' + number of comments}}{\text{number of followers}} \right) \div \text{number of posts} \right\} \dots \text{Formula 2}$$

Next, for equation 4, we introduce the calculation method for the ‘FF ratio,’ which is one of the important indicators for X.

$$\frac{\text{Number of followers}}{\text{Number of followings}} \dots \text{Formula 4}$$

As described above, the ‘engagement rate’ and ‘FF ratio’ are combined to derive the ‘influencer index,’ which is used to extract high-quality influencers from the followers of Company I's Instagram account.

In order to quantify the degree of interest that the extracted influencers have in I Company's posts using the ‘influencer index,’ this study proposes the ‘like rate.’ The like rate is an indicator that quantifies the degree of interest that influencers have in a post, and represents the ratio of likes per post for each influencer. The formula for the like rate is shown below.

$$\frac{1 \text{ Number of 'likes' per post by influencer}}{\text{Total number of posts}} = \text{Like rate} \dots \text{Formula 5}$$

2.3 Centrality analysis

To perform centrality analysis in a follower network, we use the adjacency matrix in graph theory from the follow-follower relationship. Let be the nodes, and the follow-follower relationship is represented as the adjacency matrix A .

2.3.1 Degree centrality

The higher the degree centrality, the more connections a node has to other nodes, indicating that it has numerous relationships (Kanemitsu, 2003). When the network used in this study is a directed graph, degree centrality can be separated into in-degree centrality and out-degree centrality. In-degree centrality is a measure of the number of edges entering a node, while out-degree centrality is a measure of the number of edges leaving a node. In this study, in-degree centrality corresponds to the behaviour of ‘following a user,’ while out-degree

centrality corresponds to the behaviour of ‘being followed by a user.’ In this study, individuals who cite others frequently have higher in-degree centrality, while those who are frequently cited have higher out-degree centrality.

2.3.2 Eigenvector centrality

Eigenvector centrality is a measure of centrality calculated by taking into account the centrality of adjacent nodes (Bonacich 1987). This measure is an indicator that takes on larger values when a node is adjacent to nodes that are connected to important nodes.

2.3.3 Community extraction

Simply measuring the centrality of the people you follow is not enough to reveal how information spreads. This is because visualising the connections between the people you follow reveals mutual follow relationships, resulting in a structure like Figure 1. When considering diffusion, it is necessary to know what communities each person forms and belongs to. Therefore, it is necessary to divide the network into circles and squares, cutting off the weak connections, to see what kind of network structure it has (Murata 2009).

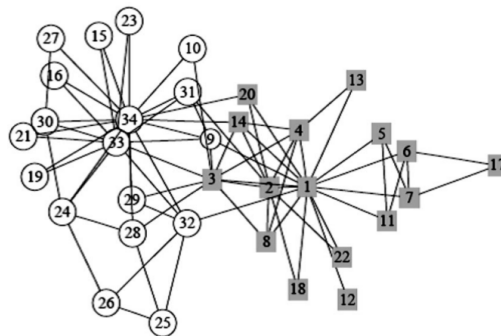


Figure 1: Example of community extraction

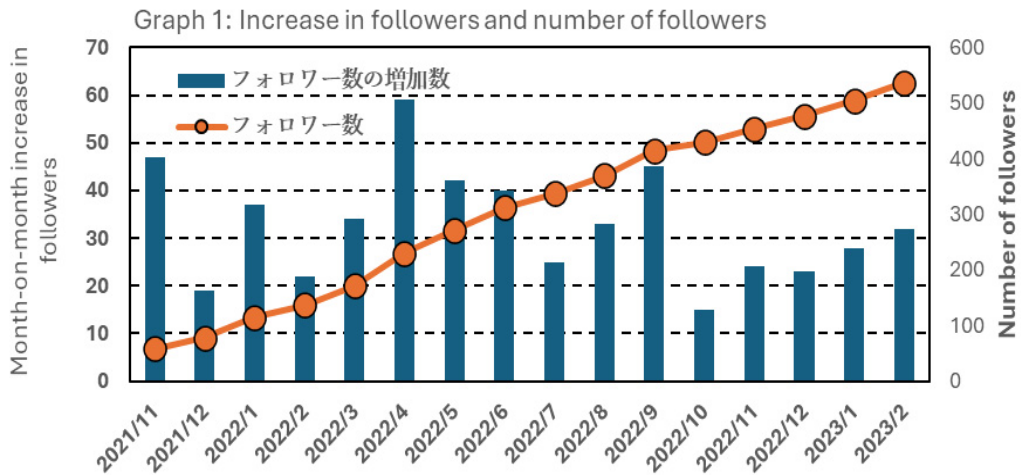
To visualise the quality of influencers, we adopted the ‘link community extraction method.’ This graph theory-based method is divided into hard clustering and soft clustering. The Louvain method is commonly used for hard clustering, but since this method does not allow community overlap, it cannot accurately express the influence of influencers. Therefore, in this study, we introduced the link community extraction method, which is a soft clustering method. This method clusters links based on edge similarity and visualises influencer influence. Specifically, it leverages the feature that ‘nodes can belong to multiple communities simultaneously’ to calculate ‘community multiplicity’ and evaluate influence.

3 Results

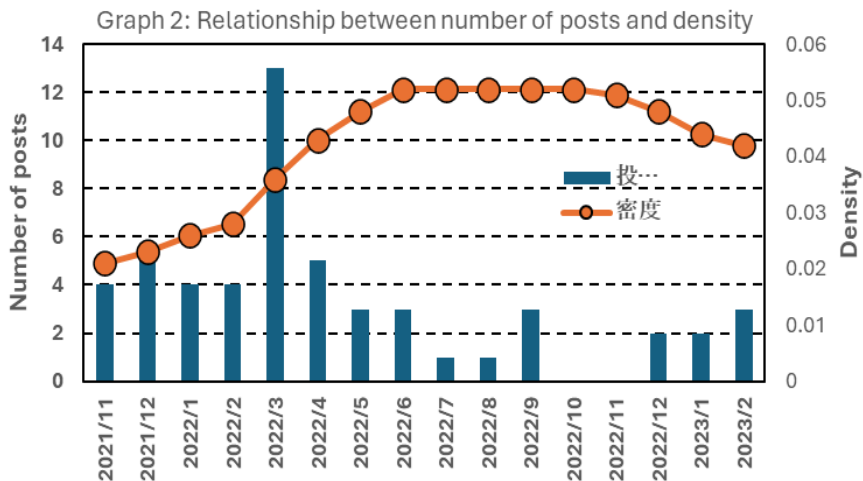
3.1 Overview of the follower network

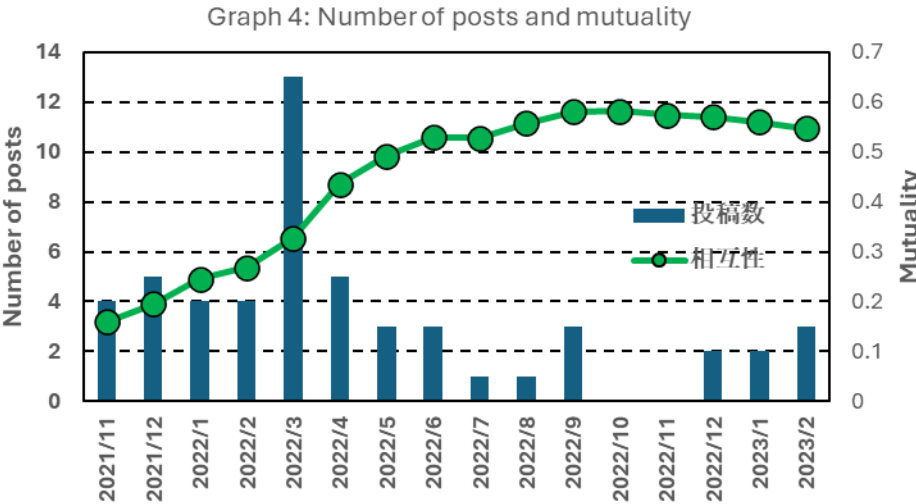
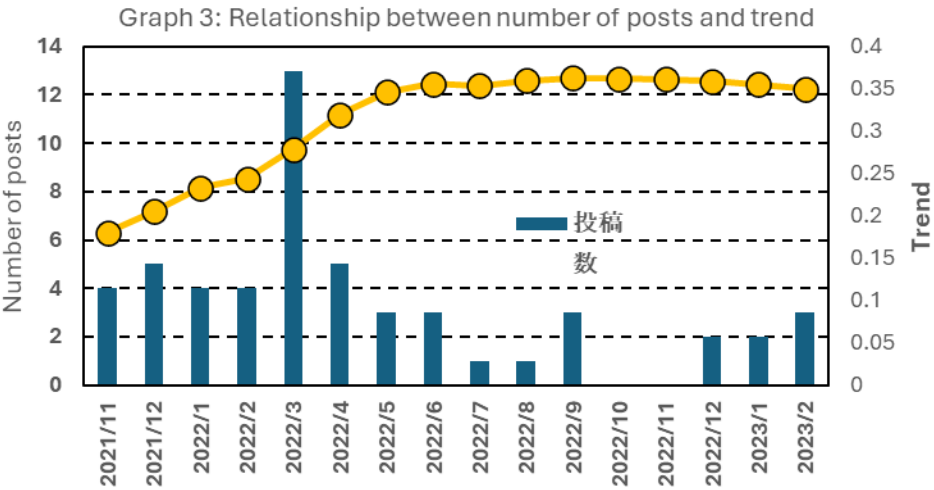
Graph 1 shows the relationship between the month-on-month increase in followers and the number of followers. Fifty followers were gained in the month when activities began, but these were employees who used Instagram personally and existing customers. From the second month onwards, sales activities were conducted without deliberately mentioning to sales targets that promotional activities were being carried out on Instagram.

Graph 1 shows that the number of followers has increased steadily.



Comparing Graphs 2 and 4, it can be seen that when the number of increases is low, there were no new posts during that month. Graphs 2 to 4 compare density, trend, and interactivity with the number of posts.





As shown in Graphs 2 to 4, when comparing the density, transitivity, and mutuality of the entire network with the number of posts per month, the density, transitivity, and mutuality increased significantly in March 2022, when the number of posts per month was the highest at 13. On the other hand, there were no posts in October and November 2022, and during those two months, the values of the three variables decreased slightly. In particular, density, which had been stable at 0.5 or above, dropped to around 0.4 after the month with no posts.

3.2 Results of Influencer Index and ‘Like’ Rate

As mentioned above, we defined influencers as ‘users with 1,000 or more followers’ and applied the influencer index to users with 1,000 or more followers among all followers. Note that 30.4% of all followers of Company I had 1,000 or more followers.

Table 1 shows the top 15 accounts with the highest influencer index. In addition, we calculated the 'like' rate, which quantifies the level of interest in I Company's posts for each influencer.

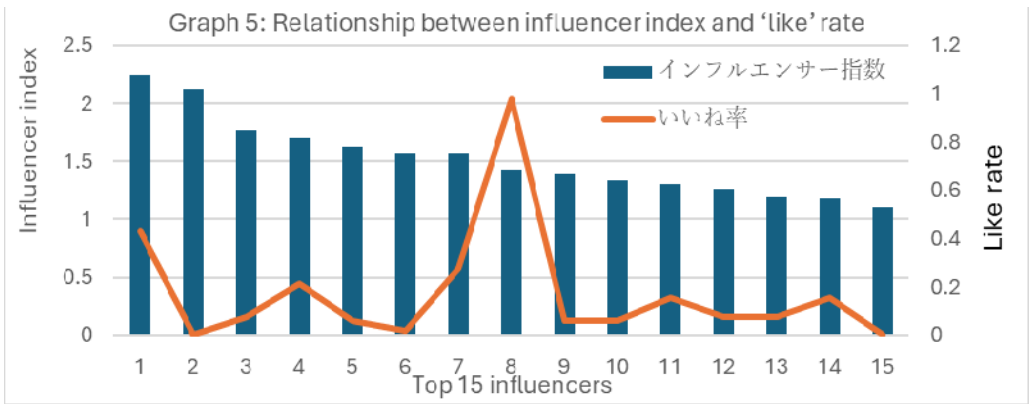
Engagement rates of 0.05 or higher and FF ratios of 0.7 or higher are shown in red. Furthermore, in the influencer index, which combines engagement rate and FF ratio, values of 0.75 or higher are considered high. Users with values of 0.75 or higher are shown in red.

Table 1: Influencer Index and 'Like' Rate (as of February 2023)

ID	Distance from company	Number of posts	Number of followers	Number of followings	Number of likes	Number of comments	FF ratio	Engagement rate	Influencer index	Like rate
1	98	262	2129	993	3040	88	2.144	0.098	2.242	0.431
2	465	406	3298	1635	4947	16	2.017	0.1	2.117	0
3	1430	945	12000	7200	18141	110	1.667	0.101	1.768	0.078
4	48	55	5876	3800	12783	652	1.546	0.152	1.699	0.216
5	632	130	1821	1213	3339	22	1.501	0.123	1.624	0.059
6	175	112	1017	782	3992	50	1.301	0.265	1.565	0.02
7	722	437	2681	1789	2579	14	1.499	0.064	1.563	0.275
8	718	127	1018	791	2053	43	1.287	0.137	1.424	0.98
9	162	48	1256	1095	4454	125	1.147	0.243	1.39	0.059
10	53	31	1050	919	3057	4	1.143	0.194	1.337	0.059
11	981	24	1502	1304	3377	44	1.152	0.152	1.304	0.157
12	902	16	1133	1023	2531	35	1.108	0.151	1.259	0.078
13	374	715	4397	3814	2727	57	1.153	0.042	1.195	0.078
14	20	288	1113	1147	3480	45	0.97	0.211	1.181	0.157
15	1050	181	1361	1276	787	0	1.067	0.039	1.105	0

It was found that all but one of the top 15 influencers were currently working in agriculture, with the exception of one agricultural university student.

Graph 5 shows the relationship between the influencer index and the 'like' rate for the top 30 accounts with the highest influencer index. The X-axis represents the user ID of the influencer, the first Y-axis represents the influencer index, and the second Y-axis represents the 'like' rate.



Looking at Graph 5, no clear relationship can be seen between the two variables, and the graph clearly shows the characteristics of each influencer. Within this range, it cannot be said that a high number of ‘likes’ necessarily means that an influencer is influential.

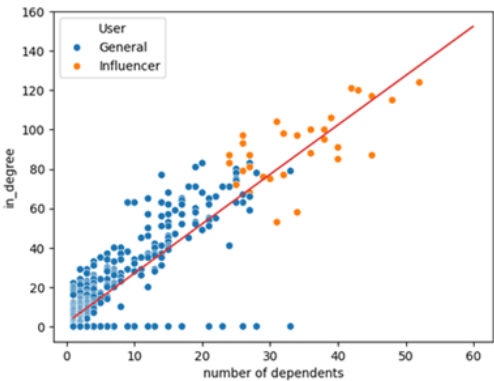
3.3 Comparison of the results of centrality analysis and link community extraction

3.3.1 Multiple relationships between each centrality and community weight

Graphs 6 to 8 show the relationship between the in-degree centrality, out-degree centrality, eigenvector centrality, and community multiplicity in the follower network during the experiment period in February 2023. Initially, there was no correlation, but a certain trend began to emerge around the fourth month, and the data from the final day of the experiment, which showed the most pronounced trend, is shown. Influencers are indicated in orange.

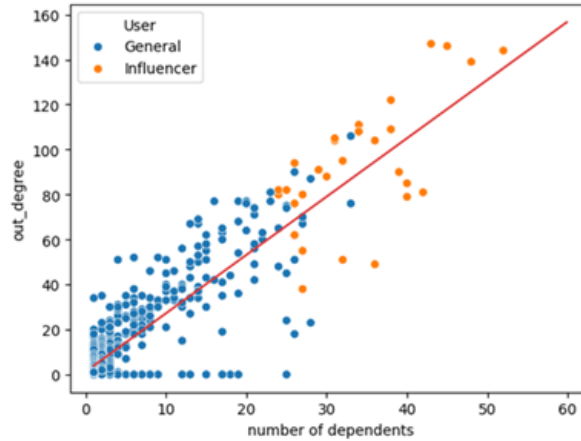
Regarding in-degree centrality, there are groups that do not form communities but have a high number of citations. Excluding these groups, a relationship between citations and community multiplicity becomes evident.

Graph 6: In-degree centrality and community multiplicity.



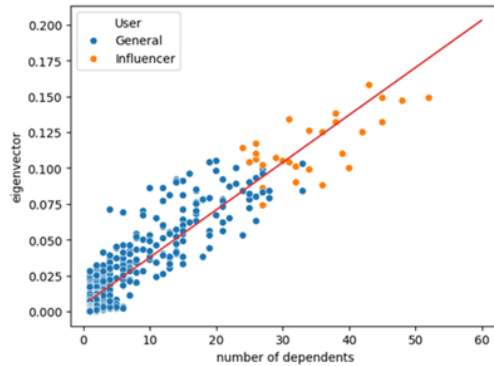
Next, from the perspective of the side being quoted, it can be seen that the structure is quite similar to Graph 6.

Graph 7: Degree centrality and community multiplicity



When viewed in terms of eigenvector centrality and community weight, the picture becomes clearer. As mentioned earlier, this centrality is an indicator of the position of members within a community. As can be seen from this, influential influencers tend to appear at the top.

Graph 8: Eigenvector centrality and community weight (February 2023)



Thus, the three centralities and the number of overlapping communities are closely related, with some overlap, but it was found that the influence increases as one moves to the upper right. From these results, the number of overlapping communities for each centrality was approximated by a regression line ($y = ax + b$). The optimal parameters a and b were determined using the least squares method. Table 2 shows the approximated regression lines, their determination coefficients, and correlation coefficients from Figures 6 to 8.

Table 2: Each centrality and regression line

Centrality	Regression line	Coefficient of determination	Correlation coefficient
Number of entries centrality	$y = 2.513x + 1.905$	0.787	0.88
Number of exits centrality	$y = 2.593x + 1.311$	0.771	0.88
Eigenvector centrality	$y = 3.313 \cdot 10^{-3}x + 4.528 \cdot 10^{-3}$	0.876	0.92

4 Discussion

4.1 Network Structure and Number of Posts

We compared the overall density, trend, and mutuality of the network each month with the number of Instagram posts. The results revealed that the overall density (0.008), trend (0.035), and mutuality (0.059) of the network in March 2022, which had the highest number of posts per month at 13, had increased compared to the previous month. There were no posts in October and November 2022, and during this period, the values of the three variables decreased to 0.001, 0.002, and 0.007, respectively. In particular, density had remained stable above 0.5 until September 2022 but decreased to around 0.4 after the period when posting ceased. This may be because, on Instagram, even if users do not interact directly, they may be connected through common followers or by taking actions on the same posts, leading to recommendations through the platform's algorithm. When posting stops, the 'hubs' that connected unknown users may have disappeared. Therefore, even if new users follow Company I, an environment where existing followers do not follow new users may have been created. Additionally, as shown by Park et al. (2021), when density decreases, information does not spread, leading to stagnation or reduction in the number of followers. Therefore, consistent posting is crucial for expanding the follower network.

4.2 Influencer Index and 'Like' Rate

The Influencer Index requires careful consideration when applied. The index combines two variables, 'engagement rate' and 'FF ratio,' but if one of these values is extremely high, the index will also be high. Therefore, when using the Influencer Index, it is important to check both the 'engagement rate' and the 'FF ratio.' It is also important to consider the context, such as the influencer's occupation and location. Companies should confirm the relevance of the influencer to their product image and select appropriate influencers to ensure that their publicity activities are effective and that appropriate information is disseminated even in regions where sales are difficult.

4.3 Centrality Analysis and Community Weight Comparison

To visualise the quality of influencers extracted using the Influencer Index, we conducted centrality analysis and community weight comparison, and found the following. Influencers have high values for in-degree centrality and out-degree centrality, frequently cross-reference each other's posts, and do so at a very high frequency.

Influencers belong to many communities and have high values for eigenvector centrality. In other words, since they have influence in influential communities, using the extracted influencers to disseminate information can potentially reach a wider audience and increase the number of followers.

Furthermore, this research on influencers was essentially revealed by Ryan & Gross (1943) and Rogers (2003). According to a study conducted by Ryan & Gross (1943) on the spread of agricultural technology in the United States, farmers obtained knowledge from sales representatives, but when it came to persuasion, they were more strongly influenced by farmers who had already used the new product. In other words, for farmers, information from influential farmers in their local community is more important than information from sales representatives. Therefore, in the agricultural industry, when seeking to promote a product, it is crucial not only for company sales representatives to conduct sales activities but also to identify influencers with influence within the industry and utilise them in marketing efforts.

5. Conclusion

Based on the results of the two analyses, the following four points can be concluded.

(1) The values for density, transitivity, and mutuality of the entire follower network increased in the month with the highest number of posts but decreased in the month when posting ceased. (2) All extracted influencers were engaged in some form of agricultural activity, such as farming or the sale of agricultural machinery. (3) The location of influencers showed the highest proportion (27%) in the Tohoku region, which is the core area of I Company's business activities. On the other hand, influencers were also found in the Kansai and Chubu regions and the Chugoku and Shikoku regions, where I Company does not have sales offices. Furthermore, the 'like' rate, which quantifies the level of interest in I Company's posts, was highest among influencers residing in the Kansai and Chubu regions at 98%. (4) The extracted influencers belonged to multiple communities and had high in-degree and out-degree centrality as well as mediating centrality.

Based on these four points, we propose methods for increasing followers on Instagram for small and medium-sized companies in the agricultural machinery industry. First, (1) post more consistently. When I Company's account was posting consistently, direct followers may have used the account or posts as a 'hub' to follow each other, even if they did not know each other. Therefore, by stabilising

the number of posts, the posts themselves could serve as ‘hubs,’ increasing connections between new users within the follower base and potentially leading to follower growth. Second, use the ‘influencer index’ proposed in this study to identify influencers and utilise them in product advertisements. As shown in (4), influencers with a high ‘influencer index’ also act as bridges between communities within their follower base. Furthermore, (2) and (3) show that influencers are mostly farmers and are concentrated in the Tohoku region (within 200 km), but also exist in regions more than 1,000 km away. For small and medium-sized companies like Company I, it is difficult to spend a lot of money on marketing in regions where they do not have sales offices. By using the proposed ‘Influencer Index’ to identify influencers and have them promote the company's products, it is possible to disseminate information to regions where the company does not have a presence and potentially acquire a large number of followers.

References

- Anggrainia, Ni Putu Nita (2021). “The impact of SNS marketing use on women entrepreneurs in the new normal era”. *International Journal of Data and Network Science*, vol. 6, pp. 769-778.
- Bonacich, Phillip (1987). “Power and centrality: A family of measures”. *American journal of sociology*, vol.92, No. 5, pp. 1170-1182.
- Erz. (2018). “Hashtags: Motivational drivers, their use, and differences between influencers and followers”. *Computers in Human Behavior*, vol. 89, pp. 48-60.
- Kanemitsu, Jun (2003), *Fundamentals of Social Network Analysis: Toward a Theory of Social Capital*, Keiso-Shobo
- Kubota, Shuhei (2018). ‘Extracting Social Issues from Social Media Using Contextual Information.’ *Web Intelligence and Interaction Research Group*, No. 3, pp. 77-80.
- Murata, Tuyoshi (2009) , “Community Detection from Networks”., *Intelligence and information*, Vol.21, No.4, pp.500-508
- Park, Gwijeong., Chen, Fangxin and Cheng, Le (2021). “A Study on the Millennials Usage Behavior of Social Network Services: Effects of Motivation, Density, and Centrality on Continuous Intention to Use”. *Sustainability*, vol. 13, No. 5, pp. 660-679.
- Rogers, Everett (2003), *Diffusion of innovation*. New York, NY: Free Press.
- Ryan, Bryce. & Neal C. Gross. (1943), *The Diffusion of Hybrid Seed Corn in Two Iowan Communities.*, *Rural Sociology*, No. 8, pp. 15-24.
- Wondwesen, Tafesse., and Wood, Bronwyn P.. (2021). “Followers’ engagement with instagram influencers: The role of influencers’ content and engagement strategy”. *Journal of Retailing and Consumer Services*, vol. 58, pp.102303.