# Exploring the Sentiment and Online Review of Multilevel Marketing (MLM) Company Products

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## Abstract

Reviews and tweets posted on social media and websites offer timely opinion and feedback for companies to learn about customers' concerns. As a seller or marketer, it is important to understand what customer thinks and feel about products or services offered by the companies. This study aims to explore the sentiments of public opinion and understand the reason behind it through sentiment analysis and topic modelling approach. The first objective of this study is to analyse customer perceptions and sentiments towards multilevel marketing (MLM) company's product. Then, the second objective is to identify the primary topics of concern regarding the products shared on social media. To achieve these objectives, customer reviews were collected from multiple platforms such as social media namely Twitter, online web review i.e., Moutshut.com, Trustpilot, sitejabber.com, and e-commerce websites such as Amazon, Lazada and Shopee. Other than that, a survey was also conducted to triangulate the data and to get first-hand feedback and review from the customers. In this study, the reviews were analysed using sentiment analysis and topic modelling techniques: Valance Aware Dictionary and Sentiment Reasoner (VADER), Natural Language Toolkit (NLTK) packages, Latent Dirichlet Allocation (LDA). The findings of the study revealed that over 50% of the reviews were positive and customers were mostly shared about the product quality such as the originality, delivery and product packaging in their reviews. This study offers some insight about public perceptions towards the products from MLM company and at the same time helps in improving the products and services globally and locally.

## Keywords
Sentiment analysis, product review, topic modelling, social media, Twitter

## 1. Introduction
Amway is the world's largest direct selling company as ranked in the Global 100 list of top direct selling companies in the world (DSN, 2019). Amway, derived from 'American Way', is an American company which sells products related to health, beauty and home care commodities. Amway was founded in 1959 by Rich DeVos and Jay Van Andel and currently operating widely in more than 100 countries and territories. Amway manufactures and distributes more than 450 consumer products, which are supported by a team of scientists, engineers and technical professionals working across more than 75 Research, Development and quality assurance labs around the world. Top-selling products for Amway include "NUTRILITE" vitamin, mineral and dietary supplements, "Artistry" skincare products and colour cosmetics as well as "eSpring" water treatment system. With multilevel marketing strategy and its business model (Singh, 2019), Amway now has more than one million Amway Business Owners or known as ABOs. The three main ideas for Amway business model starts from a distributor who will recruit members that will act as a distributor or ABO. ABO is responsible as a member to sell the company's products and getting more people on board to gain

profits. The profits are earned as commissions when any ABO appointed by selling the company's products. The ABOs appointed will be downline, and once product sold by them, they will earn a bonus commission. Under Amway's business model, the income of the distributors is equivalent to their sale charts. Therefore, the distributors have been paid based on expanding the network by introducing new workers down the chain (Singh, 2019).

However, as a distributor or seller working in a direct selling company, the seller always needs to find a better strategy and knowing end to end about their products from the customers perspective. Amway's business code of conduct has restricted their ABO from selling using an E-commerce platform, however, there are still sellers who market and sell the products through these platforms such as Amazon, Lazada and Shopee. In Malaysia, Amway's management is still lacking in bringing the case to a serious level like legal action. However, there has been a case in India, where Amway India Enterprise has filed a series of suits against E-commerce websites for unfair competition with its legitimate business (Advocates, 2019). Different prices offered among ABOs created fierce competition and sometimes drive to unethical business code of conduct.

This marketing competition among ABOs has raised an action to look at the customer's reviews and perception from E-commerce platforms such as Amazon, Lazada and Shopee. The current social media marketing phenomena make it easy to gain direct feedback from users as social media is a great equalizer, where big brands can be outsmarted without making huge investments, and small brands can make big names for themselves (Zarella, 2009). Social media analytics introduced in the last few years for mining, analysing, and modelling data from social media is the motivation for this study. It can help researchers, and from a business, perspective can facilitate business practitioners to develop decision-making, business strategies, and solution frameworks using social media content. Using data analytics technique, this study aims to observe the sentiment trend of the customer's opinion on social media and extract meaningful insights from the comments and reviews.

### 1.1 Objectives

The objectives of this study are as follow:

- To analyse customer perceptions and sentiment on Amway's products and services to better understand the customers.
- To identify the customer's primary topics of concern regarding Amway products shared on social media and e-commerce websites.

## 2. Literature Review

Analysing social media data is still considered a difficult task because (Gandomi & Haider, 2015; McAfee et al., 2012): (1) of a large number of different social media platforms; (2) unstructured data; (3) of the data dynamics; and, (4) complexity of the data. Generated data, however, has yet to be treated systematically in text mining literature (Zeng et al. 2010), such as how subjective opinions, emotions, and attitudes were analysed. Social media research, especially regarding business and marketing, is now increasing rapidly. To situate this research within this evolving literature, relevant studies on the use of social media in business and brand-customer relationship were reviewed. Trainor, Andzulis, Rapp, and Agnihotri (2014) explored how social media technology influenced customer relationship management at the firm-level from 308 organisations. They found that social media technology allows firms to better meet customer needs and influenced customer relationship performance. According to Zhang, Barnes, Zhao, and Zhang (2018), the customer-brand relationship can also be achieved by examining customer participation and brand loyalty on social media. The results of this study revealed that to achieve a successful brand community, customer commitment and participation were the key elements. Ramanathan, Subramanian, and Parrott (2017) examined the role of social media in enhancing customer satisfaction and found social media reviews, such as shops reviews and product reviews, have an impact on customer satisfaction.

Sentiment analysis is also known as a private detective that listen to what other people are saying and they are everywhere. Sentiment analysis or opinion mining is often conducted to identify trends and patterns, determine the brand image, and to track stock market and financial market predictions (Daniel, Neves, & Horta, 2017; Fan & Gordon, 2014; Ghiassi et al., 2017; Chamlertwat, Bhattarakosol, & Rungkasiri, 2012). VADER is one of the python packages that can be used to conduct sentiment analysis (Gilbert, 2014). Yang (2019) in her study on the 2016 US election used VADER to determine the polarity of tweets and classified them according to multiclass sentiment analysis. The results of the study achieved good accuracy in classifying the tweets.

Topic modelling analysis is a model for discovering the hidden thematic structure from a large unstructured body of documents by analysing the words in the texts (Blei, 2012). Topics that emerge from the analysis are typically used to discover patterns, topic extraction, and sales forecasting (He et al., 2013; Li & Liu, 2017). A number of significant research studies on topic modelling across fields are depicted in the reviewed studies on topic modelling in Table 1

Table 1 Overview of literature on topic modelling in social media research

| Source | Field of study | Research on | Tools | Main findings |
|---|---|---|---|---|
| **(Li & Liu, 2017)** | Multitopic | Behaviour patterns | LDA | Retweeting patterns is related to users, content and publication time |
| **(Kim, Jeong, Kim, Kang, & Song, 2016)** | Healthcare | Topic coverage and sentiment dynamics of Ebola virus | n-gram LDA | Topic coverage on Twitter was more precise and narrower than the news media |
| **(Yıldırım, Üsküdarlı, & Özgür, 2016)** | Politics | Topic extraction on Wikipedia | BOUN-TI | Proposed a model to identify topics in a microblog post |
| **(He et al., 2013)** | Business/Food Industry | Transform data from Facebook and Twitter into knowledge | SPSS Clementine, Nvivo | Competitive analysis and text mining as effective methods |
| **Liu, Burns, et al. (2017)** | Multi-industries | Brand-related content on Twitter | LDA Mallet | Product, service, and promotions are the dominant topics of interest |

## 3. Methods

In this study, customer review from tweets, online surveys, online web reviews and e-commerce websites were collected using Python. VADER is used as sentiment analysis tools to classify text reviews and tweets text into positive, negative and neutral sentiment. For Textblob, the sentiment gathers the polarity value and subjectivity value before classifying it into positive, negative and neutral sentiments. Polarity floats range from [-1,1], whereby 1 is positive, and -1 is negative sentiment. Subjectivity float range [0,1]. Then, topic modelling is applied to the cleaned corpus using the LDA approach.

## 4. Data Collection

Customer reviews were collected from four main sourced (1) Twitter; (2) online web reviews - sitejabber.com, trustpilot.com, mouthshut.com and Amazon.com, (3)E-commerce websites - Lazada and Shopee (4) a questionnaire. An online survey was conducted to understand customers' opinion and satisfaction on Amway's products such as home care living product, nutrition and wellness, artistry skincare and makeup, energy performance drink and personal shopper's product category. The review from the web review was collected from 2010-2020 and about 360 reviews were collected from the e-commerce website. Data collected from Twitter took up the largest portion of the data where a total number of 7037 tweets were collected using Amway, Noxxa, Nutrilite and Artistry as the keywords.

### 4.1 Data pre-processing

The collected tweets contain a lot of noise such as user mentioned (@), URLs links ("https://url"), retweet (RT), hashtag (#), and also unwanted characters ("b' and b"). In the data processing stage, noise symbol or texts were removed as it does not have an impact on sentiment analysis results. Some of the tweets were found unrelated to Amway review were also removed.

For the data collected from online web review, the cleaning process is quite straight forward by removing duplicated sentences rows and blank rows that were captured during the data mining process. In terms of the online survey, the unwanted sentences such as "N/A", "-", "don't' know", incomplete data and irrelevant answers were removed. The reason of removing "don't know" from the online survey is because it was found irrelevant and not in line with the objective of the study to of collecting customers' experience about the Amway's product.

Data collected from Lazada and Shopee were translated into English as there were reviews that used mix language of English and Malay. At the end of the cleaning process, all reviews were stored in one document and retested again for duplication before a cleaned corpus was formed.

### 4.2 Data Modelling Comparison

In this stage, the polarity and subjectivity of the sentences were examined VADER and Textblob. The compound score is calculated using below equation as shown in Figure 1. Table 2 shows the ideal threshold for compound score (Adarsh R, 2019) where Neutral = - 0.05 > and < =0.05, Positive = > 0.05 and Negative = < - 0.05.

*Calculation of compound Score*

$$CompoundScore = \frac{x}{\sqrt{x^2 + alpha}}$$

Figure 1 Compound score equation

Table 2 Compound value and sentiment score using VADER

| | Unnamed: 0 | timestamp | text | polarity | compound | sentiment_score |
|---|---|---|---|---|---|---|
| 0 | 0 | 3/14/2020 4:52 | Lol.. these guys making Amway look like the s... | {'neg': 0.0, 'neu': 0.606, 'pos': 0.394, 'comp... | 0.6369 | positive |
| 1 | 1 | 3/14/2020 4:54 | Top 10 Companies In The World according to \... | {'neg': 0.0, 'neu': 0.87, 'pos': 0.13, 'compou... | 0.2023 | positive |
| 2 | 2 | 3/14/2020 5:22 | Six chapters down, 500 mL of caffeine, 40+ mg ... | {'neg': 0.0, 'neu': 0.852, 'pos': 0.148, 'comp... | 0.5106 | positive |
| 3 | 3 | 3/14/2020 5:27 | Amways a pyramid scheme ' | {'neg': 0.0, 'neu': 1.0, 'pos': 0.0, 'compound... | 0.0000 | neutral |

### 4.2 Tools Validation

The data used in this study was tested using VADER and Textblob. Based on the literature, it was found that VADER sentiments are proved to be more accurate in determining the sentiments compared to Textblob as it outperformed other tools (Hutto and Gilbert, 2014). VADER lexicons perform exceptionally well in the social media domain. In their study, the correlation coefficient showed that VADER (r=0.881) performed closely to individual human raters (r=0.888) at matching ground truth with 20 human raters. Whilst in sentiment classification, VADER (F1= 0.96) outperformed individual raters (F1=0.84) when it correctly classified the sentiment of tweets into positive, neutral or negative classes. In another study, VADER is said to be slightly more sophisticated, and have few advantages over other conventional models as follow (Fredrik and Bergdorf, 2019):

I. Pre-defined treatment of negation
II. Punctuation, i.e. three exclamation marks increase the strength of text more than just one exclamation mark
III. Capitalization, writing in capital letters changes the strength
IV. Constructive conjunctions, such as 'but.'
V. Strengthening adverbs such as 'awfully good.'
VI. Emojis and emoticons

To evaluate the sentiment intensity of the sentences with and without exclamation marks, one sample of the review was tested with a capital letter and exclamation marks and compared with a review without capital letter and exclamation marks as shown in Figure 2 (a) and (b). The compound score is observed to be higher and improve the intensity of positive value for the sentence with an exclamation mark.

```
3rd Statement :
Overall sentiment dictionary is :  {'neg': 0.0, 'neu': 0.747, 'pos': 0.253, 'compound': 0.7269}
sentence was rated as  0.0 % Negative
sentence was rated as  74.7 % Neutral
sentence was rated as  25.3 % Positive
Sentence Overall Rated As Positive
```

Figure 2(a) Sentiment score for the sentence with an exclamation mark and capital letter

```
6th Statement :
Overall sentiment dictionary is :  {'neg': 0.0, 'neu': 0.7, 'pos': 0.3, 'compound': 0.8275}
sentence was rated as  0.0 % Negative
sentence was rated as  70.0 % Neutral
sentence was rated as  30.0 % Positive
Sentence Overall Rated As Positive
```

Figure 2(b) Sentiment score for the sentence with an exclamation mark and capital letter

## 5. Results and Discussion

### 5.1 Sentiment Analysis

Sentiment analysis was conducted for all review throughout the platform, as shown in Figure 3. 54 per cent of the tweets show positive sentiment, and the small number of tweets (15%) had a negative sentiment. It is observed that most of the review about the product were talked a lot on review websites platform while e-commerce platform is more famous about the quality of the services offered by the sellers. Based on the word cloud of positive sentiment in Figure 4, it shows that customers were satisfied with fast delivery and good condition of the product when they made the purchase. Subsequently, derived from the negative sentiment, the word cloud of negative sentiment in Figure 5 indicates that people were not pleased with the delivery time and they were unhappy with the new product introduced by Amway. It was also surprised to see the word 'good' under the negative sentiment. The reason behind that is related to the nuances in the comments where the contextual understanding of the comments was mostly negative.

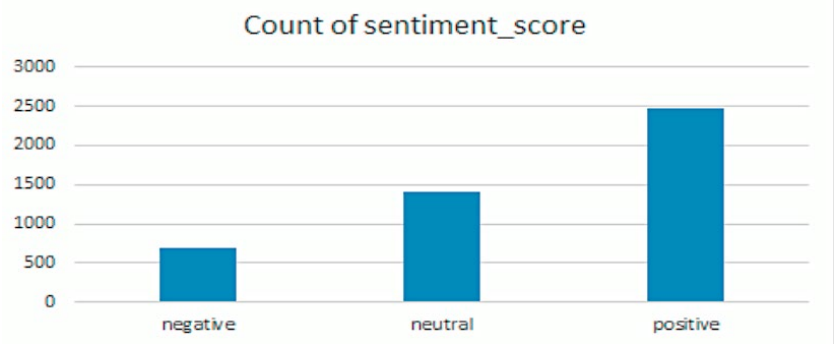


Figure 3 Sentiment on the MLM brand


Figure 4 Word cloud for positive sentiment


Figure 5 Word cloud for negative sentiment

Next, we calculated the sentiment score, compound score, positive, negative and neutral value for each sentence. The results revealed a higher sentiment score when the exclamation mark is used in the sentence as shown in Figure 6. It is understandable as the capital letter words and exclamation mark boost up sentiment value score in VADER algorithm. As observed from the result, most of the reviews that had high sentiment score were mostly related to product quality.

| | | |
|---|---|---|
| This is great news. Staff at Amway are fantastic! | {'neg': 0.0, 'neu': 0.467, 'pos': 0.533, 'compound': 0.8398} | 0.8398 positive |
| Very easy work, Very good product , fell so healthy , Quality product and So healthy | {'neg': 0.0, 'neu': 0.428, 'pos': 0.572, 'compound': 0.9241} | 0.9241 positive |
| Affordable satisfaction product , Very skin friendly,Very nutritional,Very good product,Very nice one and Sharing | {'neg': 0.0, 'neu': 0.407, 'pos': 0.593, 'compound': 0.9274} | 0.9274 positive |
| This product can make easy job, cookers .Shampoo, protect your hair from dandruff . Bcomplex make your | {'neg': 0.0, 'neu': 0.559, 'pos': 0.441, 'compound': 0.9701} | 0.9701 positive |
| More satisfaction. Great and quality. | {'neg': 0.0, 'neu': 0.284, 'pos': 0.716, 'compound': 0.8211} | 0.8211 positive |
| Give the best what i need. Valuable. The best and Great. | {'neg': 0.0, 'neu': 0.278, 'pos': 0.722, 'compound': 0.9485} | 0.9485 positive |
| Highly satisfied and Its too good not to share with others. | {'neg': 0.119, 'neu': 0.504, 'pos': 0.377, 'compound': 0.6255} | 0.6255 positive |
| Very satisfied even pricey. Advantages of the products over other choices | {'neg': 0.0, 'neu': 0.617, 'pos': 0.383, 'compound': 0.6801} | 0.6801 positive |
| Yes. I'm like organic product | {'neg': 0.0, 'neu': 0.366, 'pos': 0.634, 'compound': 0.6369} | 0.6369 positive |

Figure 6 Sample of positive reviews

The detailed analysis of negative sentiment reviews demonstrates customer's sceptical perception towards Amway as an MLM business. However, the reviews were identified were mostly written from non-consumer. This result indicates that the distributors need to step up the game and strongly educate the public about their actual business model and how it can help others in earning some income. ABOs are also responsible as front people to engage and provide correct information to the public about their business model. The challenge is that they need to strategise their marketing and selling strategy to cater to this kind of negative perception from public and non-consumer. Another

conclusion that can be derived is that the unethical selling from the e-commerce website like Lazada and Shopee should be stopped and bring forward as the negative reviews from that platform as seen in Figure 7 could taunt Amway's business image.

| | | | |
|---|---|---|---|
| Life is the worst pyramid scheme ever. Worse than Amway | {'neg': 0.474, 'neu': 0.526, 'pos': 0.0, 'compound': -0.802} | -0.802 | negative |
| This stupid bitch really tried to get me into Amway bitch cant fool me twice' | {'neg': 0.451, 'neu': 0.451, 'pos': 0.099, 'compound': -0.8623} | -0.8623 | negative |
| Amway is a Scam' | {'neg': 0.649, 'neu': 0.351, 'pos': 0.0, 'compound': -0.5719} | -0.5719 | negative |
| Yes!!! I feel so bad for the people who got duped by Amway. Most of them people v | {'neg': 0.256, 'neu': 0.651, 'pos': 0.093, 'compound': -0.6974} | -0.6974 | negative |
| amway center pls answer my dms or i will cry' | {'neg': 0.272, 'neu': 0.614, 'pos': 0.114, 'compound': -0.4215} | -0.4215 | negative |
| This is a very big disappointment, it is advertised as Amway scrub buds, which they a | {'neg': 0.121, 'neu': 0.879, 'pos': 0.0, 'compound': -0.5542} | -0.5542 | negative |
| I received empty refill!!! it's worst experience in Lazada shopping for me! my RM113 | {'neg': 0.352, 'neu': 0.648, 'pos': 0.0, 'compound': -0.7946} | -0.7946 | negative |

Figure 7 Sample of negative reviews

## 5.2 Factors of product review using topic modelling

In this study, 10 topics were extracted using the LDA method. Figure 8 illustrates the 10 topics with 5 top keywords each. K is set up as 10 as it is enough value to describe topic classification based on the amount of data collected (Goswami & Kumar, 2016; Kim, Jeong, et al., 2016).

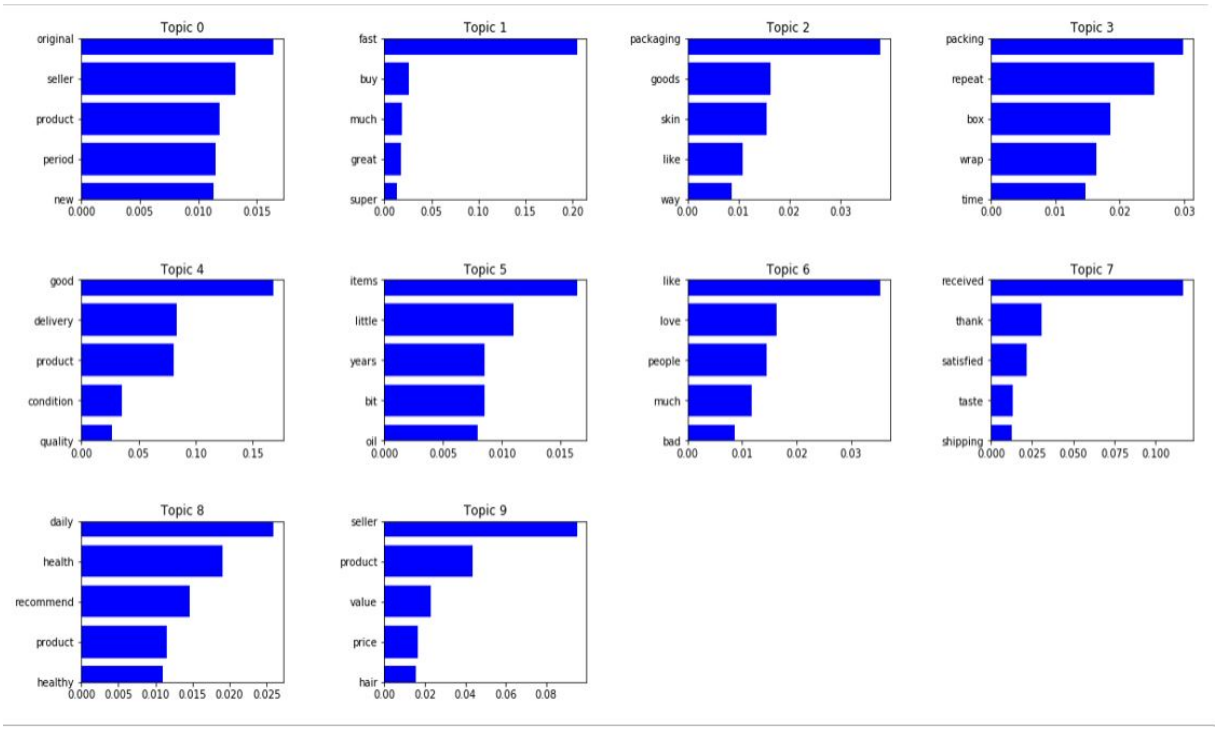


Figure 8 Topic classification graph

Based on the topic division, the first topic represents the product and seller. Word 'original' was recorded as the most significant word as it shows the products are authentic and original seller are preferred. The word 'fast' in topic 1 is labelled as about delivery based on the keyword 'delivery' and 'time'. These keywords somehow could be associated with comments from e-commerce platform like Lazada and Shoppe where fast delivery is one of the suggested

comments in the review column. Topic 2, 3 and topic 7 can be labelled as product packaging as the appearance of the keywords such as 'packaging', 'packing', and 'wrap'. It demonstrates that customers are satisfied with the way the sellers wrap their products before sending them out for delivery. These topics could also be related to the logistic company used by Amway and sellers from Lazada and Shopee. There are also 'shipping' and 'satisfied' words appeared in Topic 7 which indirectly shows that customers were satisfied with free shipping offered by some platforms.

## 6. Conclusion

The study aimed at analysing customer sentiment on MLM products and identify the topics or areas that customers talked in their review. The results indicate that over 50% of the reviews are positive and product quality, delivery and product packaging lead the emerging topic. These analyses provide company and distributors with insight not only about customer's perceptions about their product but also the reason behind the sentiment. The positive sentiment is aligned with Amway's operations on why they can successfully sustain their business for more than 40 years. Companies can gain insights not only about customer perceptions towards their products and services, but also the areas that receive the greatest number of negative customer sentiments. Besides, this study also provides insight into the primary topics of concern to customers with the aim of aiding the distributor and ABOs' understanding of customers and help improve their services. Future studies should consider the opinions from different social media platform such as Facebook and Instagram. Data from various data sources may be presented in different forms and therefore requires different sets of analysis techniques. Nevertheless, the analysis of data from other sources may provide different implications.

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