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Facial Skincare Journey:
Consumer Needs Identification to Enhance Online Marketing

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ABSTRACT

Consumer journey analysis led to efficient marketing implementation. A journey represents a path of steps and interaction between consumer and service units at each touchpoint. Dissatisfaction in the touchpoint causes a negative effect to retain a customer. Previous studies always constructed journey maps that relied on the narrative approach. According to Google, consumers always face massive websites, which is a pain point in the journey. Improving consumer buying led to the research aims: identifying consumer needs and reducing SEO pain-point using content relevance indexing. The data (social media posts from the Thai beauty communities in the year 2020) are analyzed and the authors have found that there are two need types: curative and preventive. The study can segment the 150 websites into four groups, which reduces the search space. Moreover, the significant words from the wrapping technique can be used to create keywords in the homepage introduction that match the products to consumer needs.

KEYWORDS

Consumer Journey, Journey Map, Pain Point, Touchpoint

INTRODUCTION

Taking care of physical beauty is important for people, especially teenagers. Since the face is the first body part that others see, focusing on a product or service on facial skincare contributes much revenue in this industry. Facial skincare products are unique among cosmetic products in that they are often deemed necessary by medical professionals, particularly products that offer UV protection. The global skincare products market size is projected to reach USD 183.03 billion, according to a report by Grand View Research (2019). Acne is a kind of facial disease that can be caused by an intrinsic factor, the human body, and external factors such as the weather and wearing a mask in a pandemic crisis, as proved by many skilled care experts (Sae-ra et al., 2020; Jongwook et al., 2020).

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This skin problem is present among teenagers of all nationalities, which is advantageous for skincare cosmetics. Due to the large volume of skincare products, companies continue to offer consumers innovative products for fighting the effects of skin problems, while online shops and retailers deliver good services and information to increase sales volume. Knowing that "curatives care urgently to care while preventive care can relax with time constraints" is essential for writing concisely and precisely at the homepage introduction (Kenkel, 2000). The path of finding skincare products and meeting urgent needs is highly correlated.

The customer journey (CJ) is widely used by marketers as an effective tool in strategic implication and management services (Zomerdijk & Voss, 2010; Dhruv & Anne, 2020; Andrews & Eade, 2013). The *customer journey* is a set of events that define key experiences in the life cycles of customers. The *customer journey map* (CJM) is a blueprint that represents a firm's product plan for a customer, whereas *touchpoints* are the interactions between customers and service providers. Crosier & Handford (2012) reported the benefit of using CJMs for marketers to improve customer value. Past research on CJMs had several perspectives, including design and management services, integrating customer experience, and co-design (Wechsler, 2012; Rawson, Duncan, & Jones, 2013). The customer journeys experience includes the customer's emotional, social, and spiritual responses to all individual contacts and indirect contacts with a firm at distinct touchpoints in time (Homburg, Jozić, & Kuehnl, 2017; Lemon & Verhoef, 2016). Providing customers with quality experiences depends on a firm's competency to reduce pain points; fragmented and frustrating interactions, therefore, lose revenue to the competing brand. Recently, Sharon & Aaron (2020) suggested that the patterns and drivers of consumer pre-purchase activities, purchase decisions, and post-purchase commitments may differ significantly across cultures.

Due to the rapid growth of technology and demand for high-quality service, the scope of CJM analysis always explores the difference between the *expected journey* and the *actual journey*, which aims to describe how the journey is really experienced by the customer (Følstad, Kvale, & Halvorsrud, 2013). Moreover, investigations and resolving pain points to retain customers were added to fulfill CJMs. Lazar, Feng, & Hochheiser (2010) proposed multichannel perspectives on digital services with the integration of the human-computer interaction (HCI) in a CJ context. Visualizing a CJM in a dynamic sequence of touchpoints is the most popular method in previous studies, both qualitative and quantitative (Moody, 2009; Gustafsson, Johnson, & Roos, 2005). Using CJMs, the service process investigates customer satisfaction from the beginning to the end, to improve the journey. This variation in purposes and practices on the marketer's viewpoint, however, is lacking in two crucial states: first, the stage of consuming and awareness and second, the stage of acquiring information to satisfy customer needs, wants, and expectations. These three satisfy elements are the primary driving force to customer awareness on the CJ to make the right decision. The *curative need* is a consumer need for safety, acquires the shortest path of CJ (Gustafsson, Johnson, & Roos, 2005). Google is the search engine used the most for multi-dimensional aspects (Tomasi & Li, 2015). However, there is still a problem with time-consuming, volume-driven SEO and led to Grow and Convert as a strategy to reduce the pain point with concern on the curative care (Hyam, 2020). The study, applied mathematical techniques and text mining to identify consumer pain-points at the needs stage and used the concept of "known customer pain-points to find keywords."

This paper is organized as follows; Background describes the previous research and theories related to the main components of the study, Research Method sets out a purpose framework of data collection, data analysis to construct an efficient CJM for buying facial skincare products, results, and the final section includes conclusion, limitation, and future work.

LITERATURE REVIEW

Customer Needs and Awareness

Regarding the importance of understanding consumer needs, identifying types of needs is beneficial in implementing a marketing strategy. Consumer needs may be physical or emotional, including a sense of belonging to the community and social recognition (Lilien, Rangaswamy, & Bruyn, 2017). From the physical need perspective, customers must recover from their problems without negative side effects or compromising safety. Maslow's hierarchy of needs investigated the motivation of individuals in organizations on the basis of needs (Mathes, 1981; Wynn & Coolidge, 2004; Maslow & Lowery, 1998; Herzberg et al., 1959). The theory led to many new modified needs models that have been applied in other fields, including marketing, consumer behavior, and management (Kotler & Keller, 2006). In the modern mindset, cognitive needs are expressed through a desire to understand and find meaning. Thus, knowledge appears to be the main driver behind this need. Similarly, aesthetic needs are spurred by the search for things such as beauty, balance, and form and thus imply a desire for detail and self-expression (Ward & Lasen, 2009). With regard to the five-level needs model, purchasing acne treatment products aims to satisfy multiple needs: safety, social needs, and esteem (Maslow & Lowery, 1998).

In 1993, Kano (Kano et al., 1984; Wang & Ji, 2010) elaborated a needs model to assist companies in the perspective of consumer needs. Kano's basic needs represent the fundamental things buyers normally expect from a certain product or service. As Kano's model suggests for organizations attain customer delight fostered by the fulfillment of excitement needs. The three-level requirements consist of basic needs, performance needs, and excitement needs.

With *basic needs*, the product attributes are not declared but expected, e.g., hotel cleanliness and safety, while facial skincare can cure infection without side effects. The second requirement, *performance needs*, is the product offering quality, speed, and professionalism, while *excitement needs* are unexpected characteristics of a product or service that are more powerful than the competitor, in customer perceptions. The link between consumer needs and marketing strategy is the crucial knowledge to maintain a firm's performance. Furthermore, understanding the needs for curative and preventive dimensions is also useful for marketers (Wang & Ji, 2010). Previous studies on medical care or treatment are divided into preventive and curative services for patient needs. Consumers can consume two types of services to manage their illnesses: preventive and curative care (Kenkel, 2000). *Curative care* refers to treatments such as surgery and certain types of medicines that help improve symptoms or cure the condition (Nitin et al., 2014). Although primary preventive and curative care serve similar purposes, they differ in two respects. First, curative care is more expensive and provides a greater boost to consumer health compared to primary prevention. Second, primary prevention is useful when the illness is detected at an early stage, and its severity ranges from low to moderate.

Consumer awareness is an act of making sure the buyer or consumer is aware of information about products, goods, services, and consumer rights. Consumer awareness is important so that buyers can make the right decision and make the right choices. The *stage of awareness* refers to the degree to which the consumer prospect knows about their needs, pain points, and the solutions to solve the problem. At the awareness stage of search information, consumers need to narrow down the range of choices and also get precise and concise information. So far, awareness to get information of teenage consumers always postpones on the social media channel and Google Search. The accelerated role of digital technologies and other factors such as curiosity and the pandemic prompted consumers to use online self-services when it came to their digital needs (Sae-ra Park et al., 2021; Jongwook et al., 2020). Today, a common way to find information on demand is either using Google Search or social media. As of 2021, Google has processed over 62.19 billion times searches per year worldwide (Mohsin, 2020). Every day, billions of users rely on Google to carry out their daily searches. However, apart from being a search engine, Google also provides many other services. This includes 46% of product/service search begins with Google by using organic search (Mohsin, 2020). The main reason why organic results are helpful is that organic traffic is targeted. If firms cater their results to providing a solution to a specific user query, the chances are that the product owner will be more likely to gain a new customer. Therefore, being related to Google's right side is inherent to developing a successful marketing campaign. With search engine optimization (SEO), Google gives the business ample opportunities to convert organic traffic into consumers. According to the BURST report (2020), around 71% of consumers begin their customer journeys with Google. Due to the importance of Google, brand owners focus on putting themselves at the top of the search results. This led to their selection between money-paid or SEO strategies.

Customer Journey

Customer journey (CJ) is used to describe how a consumer becomes aware of a product brand and interacts with it during the purchase funnel (Crosier & Handford, 2012; Følstad, Kvale, & Halvorsrud, 2013; Dove, Reinach, & Kwan, 2016). In essence, CJ is the summation of customer interactions with the brand owner. The journey should be tracked from need awareness to the termination or buying, with deeper analysis. It also does not necessarily end in the coveted sale or conversion. Every interaction a consumer has with a brand, whether as a customer or not, is of importance. To better understand customer experiences when they interact with the actual steps involved in a hypothetical service of the brand owner or the other candidate brand, the customer journey map (CJM) is used to visualize this aim. Hence, being able to construct a customer journey mapping and being able to use CJMs are increasing contributions from companies (Følstad, Kvale, & Halvorsrud, 2013; Dove, Reinach, & Kwan, 2016). A CJM consists of touchpoints, paths, stages, and emotions (e.g., satisfaction or dissatisfaction). The dissatisfaction caused by receiving service lower than customer expectations is called a *pain point*. Research on CJMs plays with many aspects such as process mining (Van der Aalst, 2016), comparing the expected journey and actual journey (Følstad, Kvale, & Halvorsrud, 2013), and service delivery process (Heskett & Sasser, 2010).

As digital marketers, the focus tends to be on the traffic coming to our sites or digital properties. By ignoring other channels, or offline relationships, we are missing out on valuable data of the businesses. The customers might first come across a brand through a billboard advertisement or their friends. These early stages of awareness will impact how the brand is perceived. In turn, they may have an effect on the likelihood of an organic search later on. Offline interactions range from hearing about the brand in passing all the way through purchasing an item in a physical store. These moments will influence a user's likelihood of searching for that brand or service in the future. With regard to this fact, SEO experts study the factors affecting the positioning of a website in searching results. However, Tomasi & Li proved that increasing the rankings on search engine results pages results not only in a higher number of visitors on the site but also to the increased average duration of users visiting the site, more user engagement, and increased annual sales revenue (Tomasi & Li, 2015). The pain point SEO problem induces too many studies, e.g., the development of Google Search to GAB, which expected that positioning in the GAB significantly would help build brand awareness via the website (Baye, Santos, & Wildenbeest, 2016). Some researchers still argue that it is even negative because it can lower the traffic directed to the website. A study by Baye, Santos, & Wildenbeest (2016) aimed to determine important factors that affect the positioning of the website in the Google answer box from the view of keyword structure and density. Benji proposed an issue of "pain-point SEO", on the result of the top of the funnel for a product or service, but fewer of the searches have purchase intent (Benji, 2020). Most of the brand competition is focused on high volume instead of high-intent keywords. Benji (2020) proposed pain point SEO as a strategy that described how to prioritize content ideas around high-intent keywords over high-volume keywords with the goal of driving conversions. The Grow and Convert approach in Figure 1 have the following steps:

Using the Grow and Convert approach interacts with the problems of (a) how to know a customer pain point on the CJ path and (b) how to generate the content idea for offering the keywords. Due to the popular use of Google, and also to minimize resources, the authors propose a practical framework

Figure 1. Sequence of the Grow and Convert approach (Benji, 2020)

by applying a later second layer from this search engine. The *content-relevant indexing layer* (CRIL) supports customer needs. The layer is constructed by conducting a quantitative analysis of preview messages of the top 10 pages. Figure 2 is the CRIL framework, an example of using the search "has acne" then the results from Google are the lists of URL, title, and preview messages.

Figure 2. A proposed framework of CRIL

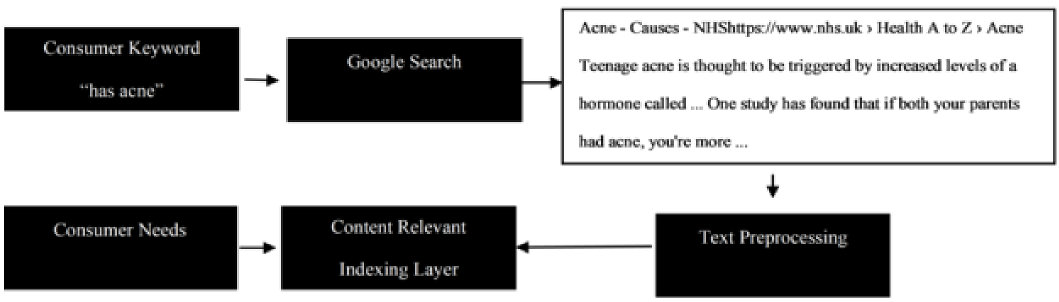
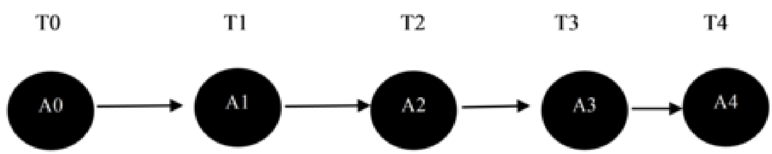


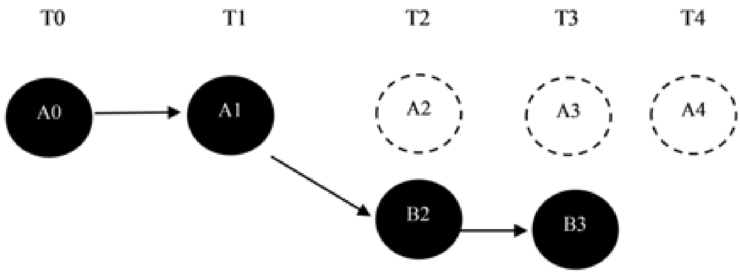
Figure 3. CJM as a hypothetical journey on the brand owner viewpoint



The aforementioned content focuses on using Google Search as a touchpoint to query data. Figure 3 and Figure 4 show the general concept of displaying a customer journey.

The notation in Figure 4 shows the meaning: $\mathbf{T}_i$ (i = 0, 1, 2, 3, 4) is a touchpoint at the i^{th} stage or time variability, and $\mathbf{A}_i$ (i = 0, 1, 2, 3, 4) is a service encounter with Brand A, while Brand B is another competitor. $\mathbf{A}_4$ is the buying touchpoint that shows the competency of Brand A to retain a customer or change the potential customer to be a customer. The discrepancy in CJM between Figures 3 and 4 is conceptualized in the influential gap (Parasuraman, Zeithaml, & Berry, 1985). This service performance gap may be mitigated in several ways. Brand owners and providers need insight into dynamic, subjective experiences at individual touchpoints and how the overall experience is shaped to alleviate customer dissatisfaction (Meyer & Schwager, 2007).

Figure 4. CJM as the actual journey of a consumer



A simple way to classify the customer journey according to the methods used for customer involvement and internal resources includes qualitative methods for mapping or co-design and quantitative methods for measurement. The qualitative methods may target individuals, such as interviews and observations, or a collaborative setting, such as the workshops for mapping or co-design (Croiser & Handford, 2012; Rawson, Duncan, & Jones, 2013).

Text Processing

The amount of qualitative data grows exponentially with the effect of technology and communication. Many forms of plain text such as posts, tweets, comments, and all other sorts of textual data get created every minute. Previously, marketing studies confirmed the CJM framework using questionnaires or observation. The rigidity of using this instrument is time-consuming for self-assessment, and the clarity of the questions and the factual answers may be in doubt. Thus, using message posts from social communities is a new way to investigate the actual behavior and expectations of customers to acquire the product or service with the right fit. The marketer can get an overview of sentiments and know-how potential lead's reaction to an online marketing campaign by analyzing the comments on the posts (Feldman & Sanger, 2007; Akash et al., 2021). Textual processing is applied to many applications, e.g., topic generating by co-occurrence clustering, knowledge extraction, and sentiment detection (Blei et al., 2003). Text preprocessing in each language may be different. For example, Thai text requires the word segment, while English text needs lemmatization, stemming, processing stop words, and punctuation removal (Jurafsky & Martin, 2000). After the preprocessing, the word vector is represented as $\mathbf{T}_i = \{w_j \mid j = 1, 2, \ldots, n\}$, whereas $\mathbf{T}_i$ has the longest variant.

Text processing in the *information extraction* (IE) viewpoint extracts structured information from unstructured text. An IE system receives the raw text and generates a set of triples or *n*-ary propositions, usually in the form of subject–predicate–object as structured information, in which the predicate is a part of the raw text that represents the relationship between the subject and some objects (Vuylsteke et al., 2010). Additionally, relation extraction is a specific case of IE, in which entities and semantic relations between them are identified in the input text. Other work by Bleier & Eisenbeiss (2015) and Reisenbichler & Reutterer (2018) employed text mining and latent Dirichlet allocation (LDA) to identify latent topics in large texts. Nadine et al. (2019) also used LDA to analyze the data conducted on customers' browsing histories and databases. Arvidsson & Caliandro (2016) and Tirunillai & Gerard (2014) used text mining to study branding and market structure. Additionally, Tirunillai & Gerard (2014) applied the LDA technique to explore dimensions of product quality to gain insight into the brand positioning. Using longitudinal data on product reviews across firms and markets, their study extracts specific latent dimensions of quality and the valence, labels, validity, importance, dynamics, and heterogeneity of those dimensions. This is remarkable that the study combines the pain point SEO (Benji, 2020; Baye, Santos, & Wildenbeest, 2016) and LDA (Bleier & Eisenbeiss, 2015; Reisenbichler & Reutterer, 2018) to minimize the path to the purchasing touchpoint.

Exploring information embedded in search queries has become a remarkable resource for valuable business insights. Short text (from search query) snippets do not provide sufficient word counts for models to learn how words are related and to disambiguate multiple meanings of a single word (Hong & Davison, 2010). In addition, the use of short messages, as well as alternating words in the text, conveys ambiguity in interpretation to lead to searches. Most people tend to use short search terms that contain words that they think will get the source they are seeking. The search term contains a single word or a related group of words, e.g., *acne* and *acne treatment*. To understand the nature of the Thai language in the use of words to indicate disease symptoms, Table 1 presents some examples.

Regarding identifying a consumer need as preventive or curative, the authors propose *marked*

Table 1. The examples of using Thai queries (Thai words) and Thai pronunciations, with comparisons to English words (via Google Translate)

Thai words	Thai pronounce	Thai to English	English word
< *มี* > < *สิว* >	< Mī > < s̄iw >	< has > < acne >	acne
< *เป็น* > < *สิว* >	< Pĕn > < s̄iw >	< be > < acne >	acne
< *ปวด* > < *ท้อง* >	< Pwd > < tĥxng >	< pain > < abdomen >	stomachache
< *ผิว* > < *อักเสบ* >	< Phiw > < xạks̄eb >	< skin > < inflammation >	inflamed skin
< *ผิว* > < *เป็น* > < *ผื่น* >	< Phiw > < < Pĕn > < Phụ̄n >	< skin > < be > < rash >	< skin > < rash >

Note: < > represents a word, e.g., " < pain > < abdomen > " in the Thai language has the same meaning as stomachache *in English.*

causality—a linguistic signal of causation present. For example, "have problems from acne" is a curative need due to the markers: *problems* and *acne*, while the sentence, "You should apply sunscreen, or your face will become blemished," is a preventive need. The information gained from consumer need identification for further search action is defined by the *lift* score for selecting a cluster of websites (Jing, Alex, & Georg, 2020). The lift score of website cluster w_i with the prior needs of consumer n is defined as

$$\mathrm{Lift}(w_i|n) = \frac{P(w_i \mid \mathrm{need})}{P\left(w_i\right)}$$

where n can be the curative need or the preventive need with prior detection from consumer needs and w_i; $i = 1, 2, 3, \ldots, k$ is any cluster of websites that satisfy the need.

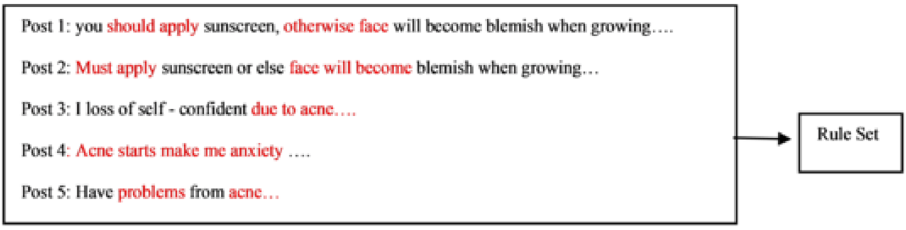
CLUSTERING AND FEATURE WRAPPING

Clustering Rule to Identify Curative Need and Preventive Need

To identify curative need (CN) and preventive need (PN), the research constructs a set of regular expressions for rule-based recognition. The regular expressions are based on association rule mining (Luna et al., 2017; Zhao et al., 2020). According to the expression $X => Y$, which means the word Y can appear when the word X appears, let $R = \{RE1, RE2\}$; where $RE1$ and $RE2$ are two strings that play the roles for retrieving and detecting, for example, $RE1 = (X, M, Y)$, in regular expression style, or $RE1 = \{ < \mathrm{key1} > < \mathrm{option1} > < \mathrm{key2} > \}$ as a sequence of words. If any string (10 grams length) from textual data is satisfied with $RE1$, then $RE1 => PN$. This concept is also applied to $RE2$. $RE1$

and *RE2* are generated by a learning sample of Dataset 1. The output from this step will provide two classes of consumers with respect to need classification by using rules as demonstrated in Figure 5.

Figure 5. The sample posts to learn by experts to generate the expression rules



Regression Analysis

The authors propose to use the regression analysis aims only to explore the weight of facial symptoms that affect the CN of the consumers. The steps for preparing the data (100 posts from consumers) to perform the task include:

1. Construct a set of words as a vector or a popular name, bag-of-words with TF-IDF. According to the study focused on facial skincare products, the relevant word set is *RW* = {acne(noun), rash (noun), dry (adjective), dull (adjective), blackhead (noun), blemish (noun), peel (noun)}—these specific terms, facial skin characteristics, have been observed from general facial skin symptoms. Thus, Dataset 1 is extracted from the relevant words and assigned to matrix *X* with a size of 100 × 7.

$$\mathbf{X} = \begin{bmatrix} x_{1,1} & x_{1,2}\cdots & x_{1,7} \\ : & : & : \\ x_{100,1} & : & x_{100,7} \end{bmatrix}$$; for example, x_{54} represents the "dull skin" value of Consumer 5.

2. To explore the significant weight of each feature (x_1, x_2, ... x_7), the study assigned *CN* a value of 1 and *PN* a value of 0, to construct vector **y** ($\mathbf{y}_i$ = 0 or 1). Finally, the equation for further analysis represents is represented by the following matrix equation:

$$\mathbf{y} = \mathbf{x}^2 + \boldsymbol{\mu}$$

and the prediction model is:

$$\hat{y}_i = \hat{2}_0 + \hat{2}_1 x_{i1} + \hat{2}_2 x_{i2} + \ldots \hat{2}_7 x_{i7} + \mu_i \text{ ; i = 1, …, 100}$$

(We used multiple regression instead of logistic regression due to the objective of the simple extraction of each feature).

Detecting reasoning in which given values are either true or false, but only true values are given (Zadeh, 1965). For example, "a healthy person" if saying a person is depressed, then the degree of depression is a variable that cannot be determined with a *yes* or *no*. A study by Kaufmann & Graf (2012) applied fuzzy logic measures like the degree of membership to be an active customer. Fuzzy logic is more practical for human decision-making. The system applies the weighted effect of X_i on

Y (*CN*) to construct the crisp set values: moderate ($p = 0.05$), substantial ($p = 0.01$), and severe ($p = 0.001$), for further execution by the inference engine to generate output linguistic variables.

Feature Wrapping

Due to the data problems: high-dimensional, sparse, and redundant, using the feature warping paradigm is leads to overcome the issues (Akash et al., 2021). The feature warping idea is conducted on the bottom-up management by aggregating the features that highly correlate to be the same group before further process. In fact, that this idea is used widely as many names such as latent semantic analysis and principal component analysis (Griffiths & Tenenbaum, 2007). This concept has been used in many fields, such as natural language processing, text processing, and marketing analysis (Akash et al., 2021). To construct Dataset 2, the authors collected 150 preview messages as raw data, then passed the data to the Thai language preprocessing step. Consequently, word-to-vector extraction (i.e., starting with a noun, verb, or adjective) was processed to formulate matrix data for further analysis. Finally, the system used principal component analysis (PCA) as a feature wrapping to reduce the dimensions of data size from m to k ($k < m$).

Consider the following general problem. Since a vector is a set of random variables, $x_1, \ldots, x_m$, it has a large number, m. A large number of features affects time consumption and complexity analysis. If we can set the variables, $z_1, \ldots, z_k$ as:

$$z_i = \sum_{j=1}^{p} w_{ij} x_j \text{, for all } i = 1, \ldots, k$$

then the number of the transform variable k might be only 10% or 5% of the original number m. The new variables (z_i) must be satisfied that they can preserve as much information as possible. To meet the condition of preservation of information, the expected value of the squared error of original data and transform data must be minimized, that is, by reconstructing $\mathbf{x}_j$ as a linear transformation $\sum_i a_{ji} z_i$, minimizing the average error.

$$E\left\{\sum_j \left(x_j - \sum_i a_{ji} z_i\right)^2\right\} = E\left\{\mathbf{x} - \sum_i \boldsymbol{a}_i z_i^2\right\}$$

For simplicity, consider only transformations for which the transforming weights are orthogonal and have a unit norm:

$$\sum_j w^2_{ij} = 1 \text{ for all } i \text{, and } \sum_j w_{ij} w_{kj} = 0 \text{ for all } i \neq k$$

From the standpoint of content-relevant indexing, the benefit of clustering m features into k factors is the naming of the factors based on their semantic basis and characteristics. Meaningful names for the extracted factors should be provided. One factor-naming technique is to use the top one or two loading items for each factor. A well-labeled factor provides an accurate, useful description of the underlying construct and thus enhances the clarity of the analysis. For example, z_1 is *customer involvement*, which consists of three customer attributes: *prosumer*, *co-creation*, and *recommendation*, while z_2 is customer engagement, and z_3 is customer value. Thus, the authors can claim that the customer is characterized by engagement as a dominant symbol (z_2 is a maximum absolute value).

RESEARCH METHODOLOGY

Data Selection

The study examined Dataset 1 by collecting text from consumer posts as narratives and recommendations from Thai members of puntip.com (data was collected during November 2020–June 2021, with 100 posts from skincare, skin secret, acne problem, and skincare communities). Message selection used the concept of the customer journey and the domain of facial skincare problems. Dataset 2 was examined by collecting short preview messages from Google Search with each query. The preview message (Table 2) acts as an introduction with the goal of addressing user queries.

Table 2. Example of the output from Google: title, URL, and preview message from the query, "has acne"

URL	Preview Message (PM)
Acne-NHS https://www.nhs.uk › conditions › acne	Things you can try if you have acne. These self-help techniques may be useful: Do not wash affected areas of skin more than twice a day. Frequent washing …
Acne-Symptoms and causes-Mayo Clinic https://www.mayoclinic.org › syc-20368047	12 Sept. 2563—Bacteria; Inflammation. Acne typically appears on your face, forehead, chest, upper back and shoulders because these areas of skin have the ...
Acne: Causes, Risk Factors, and Treatment-Healthline https://www.healthline.com › health › skin	Your skin has tiny holes called pores that can become blocked by oil, bacteria, dead skin cells, and dirt. When this occurs, you may develop a pimple or "zit" …
Acne: Causes, treatment, and tips-Medical News Today https://www.medicalnewstoday.com › artic...	Human skin has pores that connect to oil glands under the skin. Follicles connect the glands to the pores. Follicles are small sacs that produce and secrete liquid.

Data Preparation

According to the characteristics of the Thai massages, which are quite different from the English language, the sequences of the preprocessing are:

1. Automatic word segmentation and filtering incorrect word segments due to misspelling, ellipsis, and using other symbols in the Thai language via language pattern recognition
2. Translation from Thai to English using Google Translate
3. Lemmatization, stemming, processing stop words, and punctuation removal
4. Extract relevant words to feature vectors

RESULTS

Sub-Task 1 Aims to Identifying PN or CN

The collection of Dataset 1 was constructed from 100 sample post messages using stratified simple random sampling with equal allocation from the four social communities as the strata of sampling design (reference in data selection section). From Dataset 1, the authors observed language behavior and then created rules for the classification of types of consumer needs. The results of the work are illustrated by the following keywords:

Keywords to identify PN = { " < should/must > < apply/use > …. < otherwise >, < should/must > < apply/use > …. < or else >, < should/must > < apply/use > … < will become > "}

A regular expression to both extract and classify the need type (*PN*) is:

RE1 = (*X*, *M*, *Y*), where *X* = { < should/must > < apply/use > }, *M* is any substring, and *Y* = { < otherwise >, < or else >, < will become > }

The exploration of the problematic keywords (*M*) and the set of related words *X* to construct *RE2* is:

RE2 = (*X*, *M*) or (*MX*), where *X* = { < due to >, < cause >, < problem >, < sensitive >, < appear >, < affect/effect >, < stress >, < confident >, < anxiety > }, and *M* is any substring contain facial problem keywords = { < acne >, < rash >, < dry >, < dull >, < blemish > < blackheads >, < peel > }

The 100 posts in Dataset 1 were classified as 85% CN, 13% PN, with 2% as both CN and PN. Knowing the type of need empowers further information searching at the initial stage of the journey.

Sub-Task 2 Aims to Explore the Weights of Facial Skin Symptoms

Using Dataset 1 to analyze the regression method has found the results as shown in Table 5. The seven independent variables are *acne*, *rash*, *dry*, *dull*, *blackhead*, *blemish*, and *peel*. Consequently, the system formulates vector **y** using this criterion: If a message is of type *CN*, then $\mathbf{y}_i = 1$; else, $\mathbf{y}_i = 0$.

Table 3. The results from the regression analysis

Variable	Coefficient	Standard error	*t*-statistic	*p*-value
Intercept	0.2967	0.1511	1.9629	0.0624
Blackhead	0.1637***	0.0353	4.6407	0.0001
Rash	0.0248	0.1750	0.1420	0.8884
Dry	0.0179	0.0741	0.2415	0.8114
Dull	0.2386	0.2583	0.9238	0.3656
Acne	0.3717*	0.1550	2.3983	0.0254
Blemish	0.1014	0.1643	0.6172	0.5434
Peel	0.6097*	0.2771	2.2005	0.0386

Remark: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The results from Table 3 suggest that: (a) *blackhead* has a severe impact on *CN*, (b) *acne* has a moderate impact on *CN*, and (c) *peel* has a moderate impact on *CN*.

Sub-Task 3 Aims to Classify the Websites on the Semantic Context

The authors used a query expression, *has acne*, to construct Dataset 2 and then formalized it to a matrix of size 150 × 22—150 websites and 22 words (i.e., features) for further feature reduction analysis. General guides included a rule of thumb that suggests having at least 100 cases or greater is needed for factor analysis (Comrey, 1973; Sapnas & Zeller, 2002). This state-of-the-art shows that 22 features are wrapped into four factors with a KMO correlation of 0.67, while the commonalities are 0.798, 0.741, 0.732, and 0.701, and Bartlett's test of sphericity (Bartlett, 1950) provides a chi-square output that is significant (chi-square = 473.79 with $df = 276$; $p < 0.001$). The results are considered adequate for analyzing the EFA (Hair et al., 2014). Additionally, the components of the four factors are:

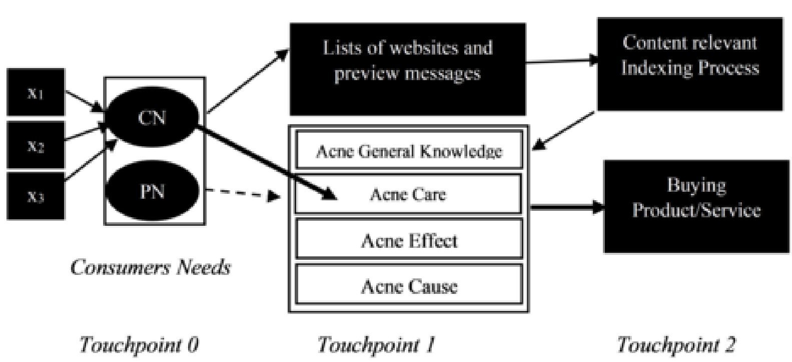
Table 4. The results of the component factor score matrix

ID	Website	Acne general knowledge	Acne care	Acne effect	Acne cause
1	https://www.nhs.uk › conditions › acne	2.7547	-0.7168	-0.3992	-0.0302
2	https://www.mayoclinic.org › syc-20368047	-0.3643	-0.1162	2.6006	-2.1825
3	https://www.healthline.com › health › skin	-0.0361	-0.3758	1.4876	-1.4030
4	https://www.medicalnewstoday.com › artic ...	-0.5445	0.4822	1.3990	-0.6420
5	https://my.clevelandclinic.org › 12233-acne	0.1096	2.0676	1.0496	-0.1209
6	https://www.nhsinform.scot › acne	-0.5464	0.0182	-0.3910	0.9571
7	https://www.aad.org › acne › derm-treat …	0.8861	0.2423	-0.7015	-0.6588
8	https://kidshealth.org › teens › acne	-0.1439	-0.5304	0.7146	0.0704
:	:	:	:	:	:
150	https://fitjunctions.com › pimple-workout > Solve problems ...	0.6894	0.5039	-0.9095	0.0287

Table 5. The results from partition the websites

Group label	Frequency
Acne general knowledge	43
Acne care	39
Acne effect	34
Acne cause	34
Total	150

Figure 6. The customer journey map which reduces pain point SEO in the context of consumer need



F1 = {*type*, *comedone*, *blackhead*, *aware*}
F2 = {*safe*, *advice*. *prone*, *recover*}
F3 = {*reduce*, *problem*, *inflame*, *help*, *treat*, *annoy*, *effect*, *pimple*, *cause*}
F4 = {*symptom*, *result*, *irritate*, *disease*, *solution*}

Consideration to the physical features in semantic view of *F1–F4* by naming, "acne general knowledge", "acne care", "acne effect", and "acne cause." Besides, to partition the features into four factors, the score coefficients are combined with standard scores of *F1* to *F4* for each entity. The following results show how to identify the dominant of each website.

The results in Table 4 show that entity ID 1 of the website www.nhs.uk has the highest absolute value (2.7545), thus, this website has a dominant knowledge of acne in general content. In addition to the website fitjunctions.com is classified as *acne effect* due to the value of the factor *acne general knowledge*. The frequency of websites in each category, shown in Table 5.

The results from previous sections can be summarized in the effective customer journey plan as Figure 6.

The labels in Figure 6 represent the meanings: x_1 = *blackhead*, x_2 = *acne*, and x_3 = *peel*. The visualization of CJ in the figure suggests that for any consumer who uses the query *has acne*, the results will be the list of 150 websites. After the process of content-relevant index creation (apply from the value of loading factor), consumers with CN can access a website that satisfies their need

Table 6. The descriptive statistics from the volunteer group (30 teenagers)

First touchpoint	Frequency	Type	Frequency	Number of website access to read	Value
Friend or family	8	PN	7	minimum	3
Doctor or pharmacy	1	CN	23	maximum	12
Google search	18			average	6
Beauty blogger or reviewer	1				
Shop (beauty agent)	2				

to purchase products or services to solve their problems.

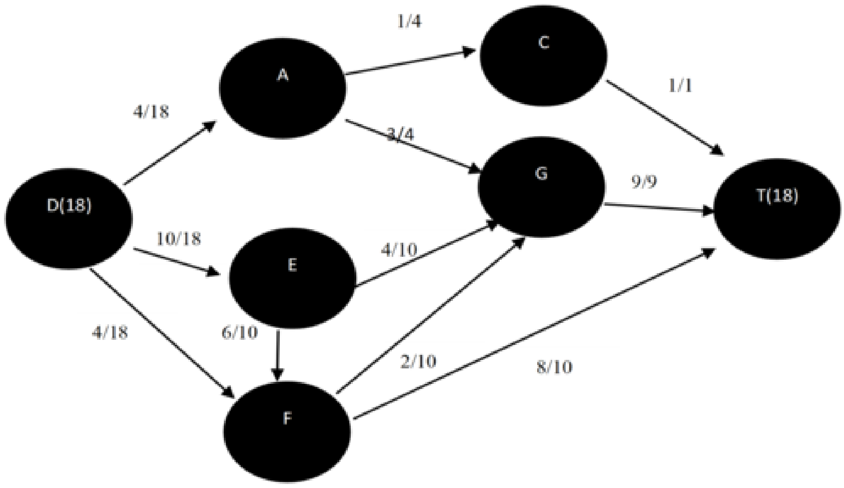
Sub-Task 3 Aims to Confirm the Research Experiment

To review and confirm the robust system, the authors contacted 30 volunteer teenagers (supported by the central limit theorem, a sample size of 30 can represent the teenage population), using open-ended questions that ask: (a) what type of facial skincare need (CN or PN); (b) the first touchpoint to access the information to purchase caring product or service; (c) how many websites were read when using Google Search; and (d) tracing their journeys from finding the first information to the final touchpoint (i.e., buying). Table 6 shows the descriptive statistics from Questions 1–3.

This study selected only the journey of 18 respondents who had CN and used Google Search as the first touchpoint. Figure 7 represents the chance of each path in the CJM.

The labels in the touchpoint in the CJM represent: A = friend or family, B = doctor or pharmacy, C = shop (beauty agent), D = Google Search, E = social media channel, F = beauty blogger or reviewer, G = brand fan page, and T = buying touchpoint. The CJM shows the path probability between two consecutive touchpoints. For example, there are ten customer journeys from D $\rightarrow$ E, four from D $\rightarrow$ A, and four from D $\rightarrow$ F. The CJM with long path or loop trapping has negative effects for both consumers and product owners. The long path journeys may be caused by a lack of

Figure 7. A customer journey map with Google Search as the starting touchpoint (construct from the volunteer group)



information or overloading information, which is the pain point of the SEO. Due to the results in Table 5, the authors can conclude that if the consumer has CN and wants to read the information from our purpose system,

$$\text{Lift}(w_i|\text{CN}) = \frac{P(w_i \mid \text{need})}{P\left(w_i\right)} = \frac{P(w_i \mid CN)}{P\left(w_i\right)} \frac{1/39}{1/150} = 3.85\ (\cong\ 4).$$

Lift-weight refers to the fact that if there is a prior type of customer need, the chance of getting the satisfaction website is four times higher, relative to the unknown. From this sample data set, it can be seen that if Google Search gives users quick access to the right information to purchase their products, all 18 consumers will be able to access the buying touchpoint.

CONCLUSIONS, DISCUSSION, LIMITATION, AND FUTURE WORK

Conclusions

Acne is considered to be a disease. In addition to having physical and emotional effects, stress, anxiety, and a lack of confidence are also common. With regard to the theory of needs, acne problems also present barriers to careers and social interactions (Herzberg et a., 1959; Maslow & Lowery, 1998). Acne problems often occur among teenagers due to internal factors and external factors such as weather or wearing a mask during the COVID-19 pandemic. Studies by Sae-ra et al. (2020) and Jongwook et al. (2020) on skin problems found that "the skin temperature, redness, hydration, and sebum secretion were changed significantly after 1 and 6 hours of wearing a mask. Skin temperature, redness, and hydration showed significant differences between the mask-wearing area and the non-mask-wearing area." People who have acne need to buy products immediately for curative care. Most people like to ask their friends or find information via Google Search. Knowing consumer needs will result in timely and accurate searches to inform purchase decision-making (Baye, Santos, & Wildenbeest, 2016). This research can provide a guideline for finding the needs of acne products from the initial state of *CJ*. The rule identifications *RE1* and *RE2* play an important role in assisting with additional website acquisitions (Luna et al., 2017). Additionally, the experiment can classify 150 websites into four groups: *acne general knowledge*, *acne care*, *acne effect*, and *acne cause*. In the case of consumers who need treatment knowledge (CN), *acne care* is the group that they will seek. The contributions from the authors' CJ framework not only are simple and practical to implement but can also apply in any domain and nationality since the Thai teenagers are not different from those in other countries on the basis of problems and the capability to access knowledge via the Internet.

Discussion

Managerial Implications

The result of technological advancement, together with the pandemic, is a catalyst for consumer lifestyles to move online increasingly. Google Search is among the popular sources for obtaining information for consumption (Tomasi & Li, 2015; Mohsin, 2020; BURST, 2020). Therefore, product owners and marketers try to use strategies to get their websites to the top of search results. However, it appears that being the top-ranking website does not bring more revenue (Tomasi & Li, 2015; Hyam, 2020). According to the data in Table 6, the average website read by a consumer has six home pages to visit. This statistic led to promoting alternatives to finding information that meets the needs of solving problems. This study can provide a guideline for analyzing consumer needs through message analysis and improving Google Search results for seeking solutions via the Internet better. The lift-weight in the research experiment is 3.85, which reduces the search space from 150 to 39. Integrating consumer need identification techniques and website classification can help satisfy user requirements (Mathes, 1981; Wynn & Coolidge, 2004; Hyam, 2020). The results of this study also suggest that writing website content in the introductory section, which will appear in the header text preview message of an organic search with Google, must be given attention by marketers to satisfy customer and consumer needs.

Since the first section of a website is an important road map for the rest of the content, it conveys a lot of information to any reader. Today, most consumer brands have been using their own websites mainly as means of sharing information and content, engaging with their consumers, and showcasing their product portfolios (Steenkamp & Geyskens, 2006). More and more, brand manufacturers and marketers are transforming their websites into true sales channels (Rajiv, Alan, & Rolph, 2002). While some brands get into this direct-to-consumer (D2C) game by scooping up new entrants, others launch their own direct routes to the market (Katrijn & Jan-Benedict, 2019). Since consumer behavior is dynamic, it is necessary to follow up on their needs and wants by exploring their posts regularly, which leads to improving the content on the website to satisfy their requirements. For example, the authors find out the relevant words (*reduce*, *problem*, *inflame*, *help*, *treat*, *annoy*, *effect*, *pimple*, *cause*) in the concept of acne care, and therefore, writing the homepage introduction should use these words for the curative care products.

Theoretical Implications

Findings that the benefit of knowing that curative need is measured by the lift-weight confirm the acne problem aspects of physical need (i.e., skin infection) and emotional need (i.e., stress, loss of confidence, and anxiety) for social participation (Maslow & Lowery, 1998). The strength of the curative need to reduce the pain point in CJ (the research experiment) is supported by the hierarchy of needs, consistency theory, and reciprocity theory. On the basis of consistency theory, humans generally love consistency, which means we want our values, beliefs, and attitudes to support each other. Therefore, marketers and retailers can take advantage of this principle by conducting content based on consumer desire to fit in. The customer response feedback is consistent with the reciprocity theory: when people receive something good from someone, they are likely to repay the kindness. In addition, the contribution to reducing the pain point in Google search supports the costing theory. Meanwhile, consumers can save time while accessing the target website.

Limitation and Future Work

The experimental datasets were collected with the following constraints: (a) Dataset 1 was collected from posts (storytelling, questions, and recommendations) among the local Thai community on facial skincare, (b) Dataset 2 was collected by using a Thai query *has acne*, (c) the preprocessing step may have caused some noise, and (d) the Thai–English translation using Google Translate. The scope of the research only focused on the stage of consumer awareness of the need and the stage of how to reduce pain point SEO. However, the research is a new paradigm of customer journeys, while previous and other recent research used qualitative analysis. Further work is needed in exploring the pain point of the firms' websites in the UX design aspect. Another interesting point concerns the causal relation of two sources of buying information: *friend or family* and Google (the two reported most in Table 6) are crucial for analyzing how to enhance marketing implementation with positive effect to their customers. Using *friend or family* as a source is based on trust theory, while using Google is based on costing theory with ease of use and convenience and led to the relation network of these two sources.

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Experimental Data

The authors constructed dataset 1 from social posts from the beauty community on Facebook by using keywords extraction and dataset 2 was collected via Google Search (explanation in the data selection section).

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