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# A Feasibility Study on Adopting Individual Information Cognitive Processing as Criteria of Categorization on Apple iTunes Store*

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〈Content〉



## Ⅰ. Introduction

Mobile application is defined as a computer program designed to run on mobile devices and it may assist people in handling their daily affairs (Wan 2014; Zhang et al. 2017). App store host, such as Apple Inc. has established complete managerial policies and rules to manage numerous mobile applications. In Apple iTunes Store, until May 2018, total twenty-four primary categories and sixty-one

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secondary categories are used to classify more than 3.9 million apps. A better categorization can bring more benefits for both app store hosts and app developers, as well as for app user. The efficiency of using app stores can be improved and better managerial regulations and policies can be enabled for app store hosts. A better categorization can also maximize the discoverability of apps that may bring more profits for app developers. Moreover, it will be more convenient and efficient for users to quickly explore and locate their desired apps. Generally, the detailed information about apps are available for external users, such as app name, interface pictures, subtitles, app descriptions, updating information, developer information, related app information, etc. App developer has to make a decision about categorizing the developed app into at least one primary category and secondary category. Therefore, the category for an app represents a location in the map of app platform. Normally, the main features offered by an app, which represent the main functionalities can be divided into several collocated keywords. Those keywords also represent the core features for those apps in the same category. In other words, app description represents the features and main functionalities, which may be very useful for user's individual information cognitive processing and decision-making processing.

However, more and more classification problems have seriously affected the searching and using efficiency of app stores. Some primary categories with ambiguous meanings have affected app's discoverability. For example, first, the descriptions for category "Utilities", "Productivity", and "Reference" are not clear enough to instruct app developers to classify their apps into appropriate categories. Second, some primary categories have significant correlations, such as category Health & Fitness and category Medical, or category Newspaper & Magazine and category News. Third, based on the prior data mining results, numerous transportation-related apps have no separate category, such as subway route apps, flight schedule, car apps, etc. According to a sketchy statistics, about 1036 car apps that used to assist people in driving or managing their vehicles could be approved (Zhang et al., 2016&2017).

Another issue was that many app descriptions written in a bad way decreased the reliability and increased the misclassification risk. For example, Most of those apps with bad descriptions didn't include those top keywords, which represented their discoverability by searching would be very low (Zhang et al., 2018). Moreover, all of the app stores had no specific regulations or tunneling steps to help app developers make appropriate app descriptions. When users tried to search an app from a category, it was impossible to find any explanations about the category.

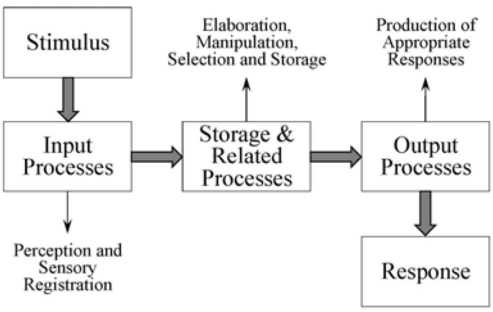
The purpose of this study focused on

discussing the feasibility of adopting individual information processing as Criteria of Categorization on app stores. Meanwhile, from an app categorization perspective, we tried to observe the effectiveness of new criteria and make more appropriate suggestions for better categorization regulations on app stores. A research approach with four research stages was performed. A series of mixed methods that involved machine learning techniques, data mining process, and statistical methods were performed. We tried to use Python 2.7 with several subsidiary libraries to write machine-learning programs for data mining process and keywords extracting process. Vector Space Model (VSM) with Term Frequency-Inverse Document Frequency (TF-IDF) and Latent Semantic Analysis (LSA) with Singular Value Decomposition (SVD) were adopted to extract keywords for mobile apps. Furthermore, the most important step was to adopt individual information cognitive processing to authenticate and record the representative functionality keywords for mobile apps from twenty-one different categories on Apple iTunes Store in order to classify them into different categories. About five thousand mobile apps from twenty-one categories on Apple iTunes Store were collected and analyzed for the keywords extracting process and classification process. We also compared our categorization results with the prior research results which were about app classification based on functionality descriptions in order to prove the usefulness and reliability of individual information cognitive processing as criteria of categorization on app stores. Further verifying process for two categorization methods was conducted by using inter-rater reliability with Cohen kappa. The results of this study showed the representative functionality keywords extracted and examined by using individual information cognitive processing could be used as the criteria to classify those apps into different categories. It may be useful for app store hosts to improve and update the current categorizations on app stores and increase mobile app's discoverability for both app developers and users.

# Ⅱ. Literature Review

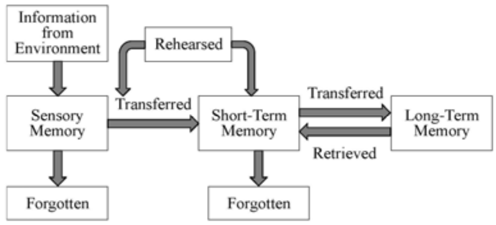
## 2.1 Individual Information Cognitive Processing

Individual information cognitive processing refers to individual's different levels of mental interpretation and cognitive processing on received message or stimuli (such as attribute information, option information, message and the related evidence or clues, etc.) and the further attitude formation activities (Cen et al., 2016; Hilbert, 2012; Altia and Tetlock, 2014; Jensen, 2011). Generally, it can be used to analyze individual's information dissemination behavior, decision-making behavior, selection and evaluation behavior, etc. Prior researchers believed that the mind could receive the stimulus, process it, store it, locate it, and respond to it. Generally, the information processing theory is considered as dealing with the learning process and analyzing process for the sequence of events that occur in a person's mind (Miller, 1956). Any new piece of information that enters the brain is first analyzed and then put through the test of several benchmarks before being stored in the memory. The basic information processing model was shown as follows.




<Figure 1> Basic Information Processing Model

<Figure 2> shows a diagram that describes the information processing model in detail. The Store Model shows the received information can be stored in any of the processing units or channels through which it passes, such as sensory memory, short-term memory, and long-term memory.




<Figure 2> Detailed Information Processing Model : The Store Model

The sensory memory or sensory register is a part of mental processing unit that can receive all information and store it temporarily or permanently. Those sensory receptor cells in human body can convert external energy signal into a message for the brain. Such energy conversion process can form individual short-term memory. It is a message attending process that requires individuals listen and pay close attention. The following encoding process can help individuals take in the message and store the message into memory bank that is ready to be called upon. If stimulus has interesting features or if it activates a known pattern, it can have an effective response. When individuals make a decision about a message, there will be two results: disposing the message or transferring it into long-term memory. Those information that stored as permanent message can be retrieved later as and when the need arises.

By summarizing prior studies, four fundamental pillars for supporting the information processing theory can be observed: thinking, stimuli analysis, situational modification, and obstacle evaluation. Thinking refers to the individual's information perceiving, storing, encoding, representing, and retrieving processes to or from his mind. Stimuli analysis means changing the encoded information in order to suit the interpretation process and understanding of decision-making process through encoding, strategization, generalization, and automation sub-processes. When there is a slight difference in the situation, individuals use previous experience and modify it to develop better ways to deal with similar problems without making the same mistakes, which we called situational modification. Obstacle evaluation means the evaluation process for considering individual's personal development, the complexity of problems, the individual's intellect, cognitive acumen and problem solving abilities because of the misleading information with dis-ambiguity and confusion (Miller, 1956; Atkinson and Shiffrin, 1968; Craik and Lockhart, 1972; Morris et al., 1977).

Nowadays, researchers have developed many theories and models for individual information cognitive processing from different perspectives. For example, from cognitive psychology perspective, some prior researchers tried to discuss individual information cognitive processing from message processing framework that focused on the phased processing mode of messages in human memory and thinking system. It emphasized how individuals code, organize, store, retrieve, use, or learn knowledge (Ariel, 1987; Miller, 2003). From the perspective of information processing, theory of planned behavior (TPB) emphasizes that behavioral attitudes and subjective norms directly affect behavioral intentions, and behavioral intentions directly determine the actual behaviors. Especially, the individual's subjective willingness depends on the individual's ability and condition to perform the behavior, that is, perceived behavioral control (Xu et al., 2012). Elaboration likelihood model (ELM) is another process theory which attempts to describe the change of attituades from two routes: the central route and the peripheral route. Individuals will try to perform the information processing in a deeper way (in a central route) in order to confirm or change the attitude when individuals have a high degree of motivation and ability (Petty, 1986; Petty and Cacioppo, 1984 & 1986; Kruglanski et al., 2012; Miller, 2005). Moreover, Heuristic-systematic model (HSM) emphasizes how people receive and process persuasive message in both heuristic and systematic ways (Albarracin et al., 2005; Petty and Cacioppo, 1986). Under the constraint of bounded rationality, individuals will selectively perceive, understand, and store information in the information cognitive processing to strengthen the individual's original attitude toward things, or weaken and even change the original attitude (Festinger, 1957; Russo et al., 2008; Chaxel et al., 2016; Van Strien et al., 2016). Therefore, in this paper, we tried to introduce individual information processing to identify the classification criteria for Apple iTunes Store.

## 2.2 App Store Categorization

Apple iTunes Store as a closed development platform provides numerous of applications and tools on iPhone, iPad, iPod touch, and Mac PC. Total twenty-four primary categories and sixty-one secondary categories can be found. However, the current categorization shows more and more problems for app searching and locating. Until now, how to classify an app into an appropriate category is still decided by app designers when they start the publishing process on Apple iTunes Store. The categorization problems were discussed by prior researchers and summarized as follows.

## 2.3 Inter-rater Reliability Statistics

Inter-rater reliability statistics can be used to identify the agreements between or among raters for some classification problems or guideline problems. Some prior researchers have used inter-rater reliability to evaluate the classification methods for mobile applications (Zhang et al., 2016 & 2017). Inter-rater reliability refers to the degree of agreement among raters that can show the reliability of related measurements or methods. If the kappa value is more than 0.8, it can be considered as perfect agreement (Smeeton, 1985). Cohen’s kappa has been used to evaluate the categorization for car apps based on data mining results (Zhang et al., 2016 and 2017). The formula of Cohen’ kappa was shown as follows.

$$Cohen\,K = \frac{P_o - P_e}{1 - P_e}$$

where $P_0$ means observed agreement; $P_e$ means chance agreement

## 2.4 Machine Learning with TF-IDF and LSA

### 2.4.1 Vector Space Model (VSM) with TF-IDF

Vector space model is widely used in

<Table 1> Summary of Categorization Error for Prior Studies

| Error Type | Description | Prior Studies |
|---|---|---|
| Miscategorized | Inappropriate introductions and features for apps | Surian et al., 2017; Lulu and Kuflik, 2016; Olabenjo, 2016 |
| Textual features missing and inappropriate description | Inappropriate textual features from app specifications (such as name, app description, features, ratings and reviews, etc.) | A. Gorla et al., 2014; Olabenjo, 2016; McMillan et al., 2011 |
| New categories required | Need new primary or secondary categories for some existed apps without proper categories. | Zhang et al., 2016; Choedon and Lee, 2018; |

information retrieval and search engines. The key to this model is the establishment of the matrix. Generally, VSM can be used to calculate the similarity of texts. The principle of VSM is based on the characteristics of the text. For example, a text has five key features (five keywords) that represent the size of this text vector is five. Each specific value is the weight of each feature. According to the characteristics of the text, the cosine of the angle between two multidimensional vectors can be characterized the similarity of two texts. The smaller the angle between the two vectors, the higher the cosine value that represents more similar of two texts. In information retrieval, TF-IDF function is commonly used for vocabulary weight calculation.

Term Frequency-Inverse Document Frequency (TF-IDF) emphasized those representative features in a given set of documents [Eck et al., 2005]. "Term Frequency" (TF) shows the word frequency or the number of occurrences of a word in a specific app. It needs to be standardized as follows in order to facilitate the comparison of different categories.

$$TF_{i,j} = \frac{n_{i,j}}{\sum_k n_{k,j}}$$

Where $n_{i,j}$ means a word frequency in app $d_j$; $\sum_k n_{k,j}$ means the sum of occurrences of all words in app $d_j$.

"Inverse Document Frequency" (IDF) is used to assign an important weight to each word and try to measure whether a word is a common word. If a word is rare, but it appears a lot of times, it can be considered as reflecting the characteristics of this category. Based on the frequency of words, the most common words have the smallest weight, but the less common words have greater weight. It shows as follows (to avoid no such word exist, add one to denominator).

$$IDF_i = log\frac{|D|}{1+|\{: n_i \in d_j\}|}$$

Where |D| means the total number of apps in a category.

$|\{j : t_i \in d_j\}|$ means the number of apps where the term appears.

$$TF- = TF \times IDF$$

The TF-IDF method is useful and more accurate to extract feature data than a regular frequency count of tokens (Baeza-Yates and Ribeiro-Neto, 1999). But sometimes, based on the TF-IDF result, it doesn't always show the representative features. Some prior researchers extracted category features by using TF-IDF on Google Play. However, some characteristics with high frequency, such as "quickly" for Books and Reference category, or "offline" for Education category cannot show the representative features of related categories (Olabenjo, 2016).

### 2.4.2 Latent Semantic Analysis (LSA) with Singular Value Decomposition (SVD)

The Vector Space Model simply searches for information based on the presence or absence of words and TF-IDF. However, there is a very big difference between "what words are written" and "meanings that you really want to express". The most important obstacles are the polysemy and synonym of words. Polysemy refers to a word may have multiple meanings. Synonym refers to a number of different words may have the same meaning. The presence of synonym and polysemy greatly affected the searching accuracy of simple word-based methods, such as VSM. Therefore, it is more useful if a model can capture the correlation between words. If a strong correlation between two words can be observed, then when a word appears, it often means another words should also appear (synonym).

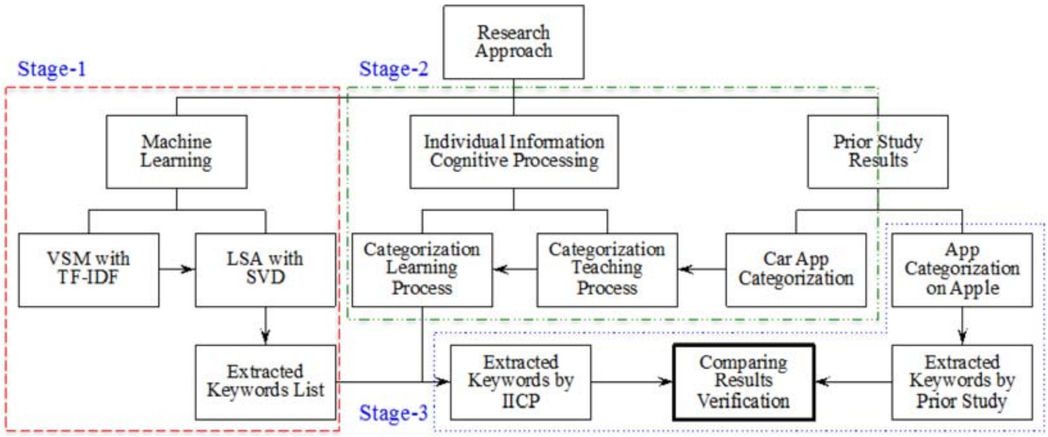
Latent Semantic Analysis (LAS) uses Singular Value Decomposition (SVD) to decompose the word-document matrix. SVD is a method of decomposing a matrix. Singular value decomposition can be considered as finding unrelated index variables (factors) from the word-document matrix and mapping the original data into the semantic space. Two documents that are not similar in the word-document matrix may be similar in the semantic space.

Machine Learning has been widely used recently in a lot of research areas, such as product classification or product promotion (Kreyenhagen et al., 2014), such as classifying products with fashion brands (Kreyenhagen et al., 2014), as well as improving categorization in health subjects and sentiment analysis, such as classifying patients with mental diseases (schizophrenia) (Schnack et al., 2014). Some researchers also introduced Latent Dirichlet Allocation (LDA) to classify data and calculate text similarities (Hong et al., 2018).

## Ⅲ. Research Approach

The purpose of this study focused on adopting individual information cognitive processing as the classification criteria in order to improve the current classification method on Apple iTunes Store. Another simultaneous target was to observe the effectiveness of the new criteria from a classification process on Apple iTunes Store. By combining machine learning techniques with cognitive psychology, we developed a research approach with four research stages to identify the feasibility of adopting individual information cognitive processing as categorization criteria on Apple iTunes Store. <Figure 3> shows the research approach for this study. The results of prior studies included a verified classification method for car apps and an extracted representative functionality keywords list by mixed method for each category on Apple iTunes Store.

In research stage one, based on a data mining process that included Vector Space




<Figure 3> Research Approach

Model (VSM) with Term Frequency-Inverse Document Frequency, Latent Semantic Analysis (LSA) with Singular Value Decomposition (SVD), keyword lists for each of twenty-one categories were conducted. In stage two, by using the prior research results related to car app's categorization, we developed an individual information cognitive processing that included a categorization teaching process and learning process. Further keywords extracting process from the extracted keyword lists was performed and top three keywords for each category were extracted. In stage three, by comparing the extracted results with prior studies, the inter-rater reliability for two different methods can be confirmed. The updating suggestions for Apple iTunes Store were discussed in this paper and the verifying process would be conducted in the near future.

### 3.1 Stage-1: App Data Collection and Keywords Extraction by TF-IDF and SVD

The first research stage focused on app data collection from twenty-one categories on Apple iTunes Store and keywords extraction by using Vector Space Model (VSM) with Term Frequency-Inverse Document Frequency method (TF-IDF). From April 2018, based on the popular app lists of 21 primary categories, about 260 apps from each category were selected only except category Game, Magazines & Newspapers, and Stickers because of their secondary categories. For each app, we scraped the app name, subtitle, description, and update information that generally represented its higher profile for sensitive keywords and saved as CSV file. Total 5460 mobile app's specifics were collected and 4905 apps left after screening. The user rating and remarking comments were not collected for our data scraping process. Although some prior researchers emphasized the contributions of rating and review attributes and comments attributes on keywords extraction process, we attempted to scrap the information that was directly composed by app developers and identified by Apple. When app developers tried to publish their apps on Apple iTunes Store, they had to select and assign an appropriate category for each app. Moreover, those comments contained too much irrelevant information that may affect the keywords extraction.

By using machine learning techniques, we tried to use Python program to analyze and extract keywords from our data sets. Term-Frequency-Inverse Document Frequency (TF-IDF) as a very simple and classic algorithm can be used in the automatic Keyphrase extraction process. Generally, the important keywords for each category should normally appear several times after screening those “stop words” that are useless for finding results, such as “is”, “in”, “the”, etc. The higher the importance of a word to a category is, the greater its TF-IDF value should be.

$$\omega_n = TF_n \times log(IDF_n)$$

By using Latent Semantic Analysis (LSA) with Singular Value Decomposition (SVD), a matrix of t*d dimensions (word-document matrix) X can be decomposed into T*S*DT, where T is a matrix of t*m dimensions. Each column in T is called a left singular bet. S is an m*m dimensional matrix, and each value is called a singular value. D is a d*m dimension matrix. In D, each column is called a right singular vector. After SVD decomposition of the word document matrix X, the largest K singular values in S, and the corresponding K singular vectors in T and D will be saved. The K singular values form a new diagonal matrix S'. Total K Left singular vectors and right singular vectors form new matrices T' and D' that forms a new t*d matrix as follows.

$$X' = T' \times S' \times D'$$

### 3.2 Stage-2: Individual Information Cognitive Processing Development

One of the most important issues in individual information cognitive processing is the development or formation of concepts. Actually, a concept is the set of rules used to define the categories by which to group similar messages, events, ideas, or objects. In this study, a concept refers to the set of rules used to define twenty-one primary categories on Apple iTunes Store. It contains two main processes, the categorization teaching process and categorization learning process. By using prior research results, we selected and used the verified classification methods for car-related mobile apps in categorization teaching process and learning process.

The prior research showed that about 697 car-related mobile apps were selected after

<Table 2> Classification Guideline for Car Apps

| Category | General Features & Functions |
|---|---|
| News and basic information about car | ✧ General car information, such as model, horsepower, color, and etc.<br>✧ Car images, videos, brand logo, news, reviews.<br>✧ New cars or secondhand cars trading information, such as price, VIN code number, etc. |
| Buying and selling | ✧ Basic buying or selling information, such as car price, etc.<br>✧ Apps used as a platform for purchasing and selling new cars or secondhand cars. Allows advertising.<br>✧ Search best dealer nearby.<br>✧ Used for dealers to show their car information to customers in a showroom or online. Save customer details.<br>✧ Car loan and tax calculator |
| Driver's communication | ✧ Driver community<br>✧ To guide user how to design a car audio system, and etc.<br>✧ DIY assembly guide for restoring a classic car, communicate with others about what types of supplies need, how to start, where to go for parts and help.<br>✧ Guides users how to paint car in steps and show to friends. |
| Location service | ✧ Uses GPS, Bluetooth, and smartphone map to find and save locations.<br>✧ Uses Photo to show parking sign or street. Use note to remember. "MEMO". Use "off-line compass memory" or "Augmented Reality Technology" to find car. Parking meter alarm and notification service<br>✧ Uses "SNS" to find nearby gas stations, EV car charging station, ATM, Restaurant, reputable mechanics, highly-rated body shops, car wash locations, parking lots<br>✧ Prevents parking fines by recording the location of your parked car and receive alerts. |
| Safe driving service | ✧ Checks local traffic congestion condition<br>✧ Calculates commute time to destination.<br>✧ Auto accident report<br>✧ Event data recorder function (EDR)<br>✧ Gets local weather conditions.<br>✧ Sends an address from the Maps app directly to the Internet-connected navigation system of the vehicle to free hands<br>✧ Monitors car speed, speed warning system, acceleration, braking G graph, Car odometer, record driving information |
| A/S maintenance management | ✧ Keeps track of car maintenance/repair records, remind you of oil changes, inspections, and part replacement.<br>✧ Keeps track your MPG, part number, car specs, dealer information, car number, license number and etc.<br>✧ Uses ICloud or dropbox to sync your vehicles and notifications across all your devices.<br>✧ Confirms Car symbols, to know the indicator or functions.<br>✧ Accident call and problem confirm, SOS service, call service, and repair service.<br>✧ Introduces parts price and information.<br>✧ Helps with no-start problem or other car problem.<br>✧ Introduces car repair knowledge or maintain knowledge. |
| Renting service | ✧ Makes or cancels a booking and check its status. Choose how many passengers. Manage previous booking and favorite address.<br>✧ Tracks the vehicle on a map.<br>✧ Uses GPS to find your location as a pickup point |
| Car expenses monitoring | ✧ Calculates how much you have spent on your car and your average costs of the car per day, week, month, or per year. It can be reported and printed.<br>✧ Reminds about tax or insurance deadline.<br>✧ Monitors spending on fuel, maintenance, parking fees, insurance fees, service fees, driving fees, car washes, part exchanges, mileage monitoring, repairs, and monitoring other expenses, |

screening and classified into eight categories by using a systematic functionality classification methods verified by two rounds of inter-rater reliability with significant Cohen kappa values at 0.886 and 0.828. <Table 1> shows the classification guideline for car apps (Zhang et al., 2017).

We developed several principles based on the prior studies (see <Table 2>) and asked five participants to attend our study for one month. At the beginning, all of the participants were asked to stay together in our research room. A presentation about categorization methods for car apps was prepared well. We performed the information processing with the following steps. From step one to five showed the categorization teaching process, and from step six to eight showed the categorization learning process.

1. Gain the participant's attention. We prepared a presentation with a PPT file, which contained a car app video at the cover page. The car app video showed a locating service and safe driving service for car users. The lecturer was asked to use voice inflections.
2. Bring to mind relevant prior learning. The lecturer tried to explain how the car-related mobile app works and how to use a car app as an assistant to drive and manage a car well. The lecturer also tried to have a discussion with all of the participants about their previously using experience.
3. Point out important information. The lecturer tried to show more detailed information about a car app on PPT file and write down some keywords about the functions or utilities.
4. Present information in an organized manner. A logical sequence to categorization concepts and classification methods were shown to participants. Based on the classification guideline, the lecturer attempted to explain it from regular functionality keywords extraction method to machine learning method. Especially, lecturer was asked to explain how to find an appropriate keyword that related to the representative functionality of the category.
5. Show participants how to categorize related information. After the lecturer finished the explanations about the categorization, several representative car apps by randomly selected from different categories were presented. Moreover, lecturer explained the classification method and the inductive reasoning for car app's categorization. By flexible using those sample apps, participants can understand the truth of the conclusion for car app categorization.
6. Provide opportunities for participants to elaborate on new information. We randomly selected 210 mobile apps from twenty-one primary categories (ten apps per each category) on Apple iTunes Store. By supplying the full information about those apps, such as app name, subtitle, app

description, update information, developer, etc., participants were asked to observe those apps and tried to find out keywords and classification principles. Lecturers and researchers of this study attempted to connect the new information to something already known by participants. Furthermore, researchers tried to help participants to find out some similarities and differences among different categories.

7. Show participants how to use coding when memorizing lists. According to some mental imagery techniques, such as the keyword method, researchers tried to help participants to remember the category names of all twenty-one primary categories. Moreover, the descriptions about each category provided by Apple Developer website were also introduced to participants. By explaining the concepts and related examples for each category, researchers tried to help participant to make up some sentences in order to memorize or understand the contents of each category.
8. Provide for repetition of learning. All of the participants were asked to attend the categorization learning classes for several times. Lecturer tried to explain and state the important classification principles several times in different ways during the presentation. This process can help users form a short-term memory (STM). Moreover, in every meeting time, lecturer or researchers would show some familiar apps from previous meetings and ask participants to classify them by using related categorization methods, such as car app categorization or mobile app categorization on Apple iTunes Store. In one month, all of five participants were required to attend the meetings twice a week. A periodic reviews of previously learned categorization principles and classification methods were also scheduled and periodically performed, which may help participants to have a long-term memory.

According to the information of categorization provided on Apple developer website, we collected those information and showed them to the participants. All of the participants were asked to read and understand the categorization information. An example of detailed information about primary categorization were shown as follows, retrieved from the developer website of Apple: https://developer.apple.com/app-store/categories/.

1. Books. Apps that provide extensive interactivity for content that is traditionally offered in printed form. If you are planning a more traditional reading experience, you may want to look at publishing an iBook instead. For example: stories, comics, eReaders, coffee table books, graphic novels.

After several rounds of reading and understanding, all of the participants were asked to select the most representative three functionality keywords for each of twenty-one categories from the keyword lists extracted by TF-IDF and SVD.

### 3.3 Stage-3: Comparative Analysis for Mobile App's Categorization

According to results of the prior research results (Zhang et al., 2018), top three Stems or simple words from each of twenty-one categories were extracted by using a mixed method that included a regular statistical method, natural language processing (NLP),

| Primary Category | Number of Apps | Total Words | Top Three Stems with Frequency and Leaf | |
|---|---|---|---|---|
| | | | "Stem", (frequency) | "Leaf" or keywords example |
| Books | 192 | 54,605 | "book", (1037) | "eBook", "bookmark", "bookshelf" |
| | | | "read", (690) | "reader", "good reads", "read" |
| | | | "story", (166) | "storybook", "history", "storytelling" |
| Business | 237 | 65,761 | "business", (279) | "business quality", "business" |
| | | | "job" (226) | "job", "jobsite" |
| | | | "work" (350) | "co-worker", "workspace", "workforce" |
| Education | 239 | 81,200 | "learn", (690) | "learner", "learning" |
| | | | "kids", (420) | "kids academy", "kids creen", "kids cafe" |
| | | | "student", (261) | "students", |
| Entertainment | 239 | 61,281 | "movie", (499) | "movie", "movie" |
| | | | "TV", (528) | "MTV", "HGTV", "TV" |
| | | | "show", (372) | "show", "showtime" |
| Finance | 243 | 71,184 | "account", (334) | "accounting", "accuont" |
| | | | "money", (503) | "money", "moneycard", "papermoney" |
| | | | "bank", (706) | "banking", "firstbank", "usbank" |
| Food & Drink | 227 | 49,295 | "food", (327) | "food" |
| | | | "meal", (218) | "meals", "mealboard", "mealtime" |
| | | | "restaurant", (295) | "restaurant" |
| Health & Fitness | 237 | 95,401 | "fitness", (471) | "fitness" |
| | | | "weight", (391) | "bodyweight", "weight-loss", "overweight" |
| | | | "health", (770) | "healthier", "healthkit", "healthcare" |
| Lifestyle | 237 | 65,840 | "appartment", (135) | "apartment" |
| | | | "life", (114) | "lifestyle", "reallife", "lifetime" |
| | | | "home", (433) | "home", "townhome", "homegoods" |
| Medical | 240 | 76,366 | "medical", (405) | "medical" |
| | | | "health", (596) | "healthcare", "healthy", "healthier" |
| | | | "drug", (245) | "drugguide", "drugstore", "drug" |
| Music | 238 | 72,950 | "mucis", (1159) | "musical", "music", "musician" |
| | | | "song", (630) | "song", "songbook" |
| | | | "radio", (263) | "radio" |

<Figure 4> Prior Research Results of Top Three Stems for Each Category _ Part 1

stemming process, TF-IDF, and greedy strategy design with Max Match algorithm. The results were listed in <Figure 4 and 5>. Further expert verification process proved the extracted results to be significant reliable by Cohen kappa with a value of 0.900.

According to the results of selection from stage 3, we tried to compare the extracted

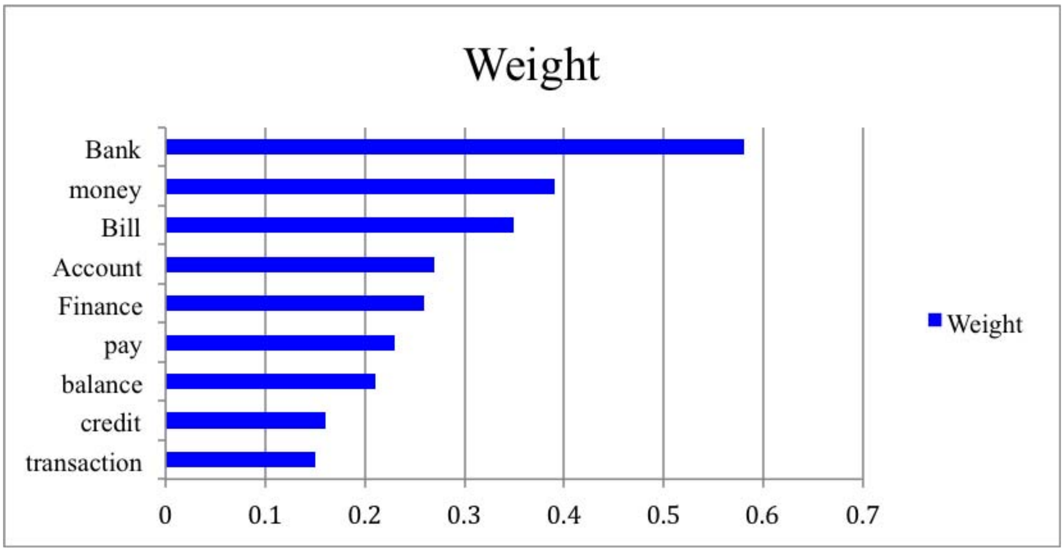
| Primary Category | Number of Apps | Total Words | Top Three Stems with Frequency and Leaf | |
|---|---|---|---|---|
| | | | "Stem", (frequency) | "Leaf" or keywords example |
| Navigation | 228 | 70,700 | "map", (813) | "map", "streenmap" |
| | | | GPS, (353) | "GPS" |
| | | | "location", (345) | "locate", "location" |
| News | 234 | 55,737 | "news", (1227) | "newscasts", "newspaper" |
| | | | "live", (324) | "live", "alive", "deliever" |
| | | | "subscription", (316) | "subscription", "subscriber" |
| Photo &Video | 238 | 74,632 | "photo", (1740) | "photoshop", "photography", "photo" |
| | | | "video", (1013) | "video" |
| | | | "camera", (316) | "camera", "camera 360" |
| Productivity | 240 | 81,018 | "automatic", (193) | "auto", "automatic" |
| | | | "note", (433) | "note", "keynote", "notebook" |
| | | | "device", (319) | "device" |
| Reference | 215 | 55,299 | "bible", (467) | "bible", "biblebook" |
| | | | "translate", (225) | "translate", "translation", "translator" |
| | | | "dictionary", (120) | "dictionary" |
| Shopping | 239 | 56,688 | "shopping", (317) | "shopping" |
| | | | "product", (236) | "product" |
| | | | "store", (472) | "store", "drugstore", "onlinestore" |
| Social Networking | 233 | 63,287 | "friend", (442) | "friend", "friendship", "friendly" |
| | | | "message", (294) | "messenger", "iMessage", "InMessage" |
| | | | "chat", (402) | "snapchat", "chatting", "chat-to-meet" |
| Sports | 239 | 65,758 | "sport", (520) | "sportsgame", "foxsports", "sportsengine" |
| | | | "ball", (445) | "football", "baseball", "basketball" |
| | | | "league", (275) | "leaguemate", "colleague" |
| Travel | 237 | 65,942 | "travel", (531) | "traveler", "traveling", |
| | | | "trip", (326) | "trip", "tripadvisor" |
| | | | "hotel", (365) | "hotel" |
| Utility | 238 | 59,721 | "device", (264) | "device" |
| | | | "calls", (414) | "call", "calling", "caller" |
| | | | "support", (200) | "support" |
| Weather | 231 | 56,530 | "weather", (1785) | "weather" |
| | | | "temperature", (212) | "temperature" |
| | | | "forecast", (609) | "forecast" |

<Figure 5> Prior Research Results of Top Three Stems for Each Category _ Part 2

results by using individual information cognitive processing method with the prior research results concluded by regular functionality selection method. The prior research tried to use a mixed method that combined a regular words extracting method with TF-IDF and verified by several rounds of Inter-rater reliability for extracted keyword stems of each category. However, further improvement was needed for the research approach. Especially, the regular words extracting method cannot extract more precise results. In this paper, we tried to introduce individual information cognitive processing to deal with the extraction process for representative functionality keywords. Individual information cognitive processing was a more rigorous scientific method for decision-making process. The comparative results would be reported and further verification process for both of two methods would be performed. The new research approach may improve the prior study and have better results for app categorization.

## Ⅳ. Data Analysis and Result

Before we performed the Latent Semantic Analysis, by using Python 2.7.10 with NumPy fundamental package and scikit-learn package, a machine-learning program was developed to perform the TF-IDF and SVD. Two main libraries were used to extract and analyze the term frequency and TF-IDF. Library "CountVectorizer" was used to convert the words in the text into a word frequency matrix. We used several functions to count the number of occurrences of each word, and to get the keywords of all the texts in the wordbag. In




<Figure 6> LSA Word Weight Example (Partial for Finance Category)

addition, by importing the library "TfidfTransformer", TF-IDF values for each word in the vectorizer could be counted. Each position in the vector corresponded to a different word and we normalized the words frequency in overall document collection and give less frequent terms more weight. We performed the keyword frequency and TF-IDF calculation together, and some additional core code was programmed.

Further Latent Semantic Analysis (also called "Latent Semantic Indexing") step was performed for information retrieval. We used Singular Value Decomposition (SVD) to perform dimensionality reduction on the TF-IDF vectors. In order to make the LSA features for each category better, we assign the weight for keywords.

First, we imported "zeros" function from numpy linear Algebra Package as well as importing SVD with library SciPy. We sorted and ignored those stop words and punctuations, such as "and", "the", "of", etc. for different categories. All of the capital letters were changed to lowercase. We sorted and ignored those stop words and punctuations, such as "and", "the", "of", etc. for different categories. All of the capital letters were changed to lowercase. All of the keywords were saved as word to title vectors. Each index word took one row, and each title took one column. Each cell represented the words frequency in the title.

After screening some apps without English descriptions, the keyword lists for all twenty-one categories were conducted. All of the five participants have accepted one month categorization teaching and learning processes. They have learnt how to classify apps into different categories. We randomly selected ten apps from each of twenty-one categories and asked five participants to classify those apps into different categories. Then we tried to verify the classification agreement among those participants in order to check whether they have already understood the categorization method. The result of Fleiss' Kappa with 0.86 (P-value=0.000) shows a "substantial agreement", which also means all of the five participants have enough individual information processing abilities, knowledge, and skills to classify apps into appropriate categories.

Once again, they were asked to read and understand the category descriptions and category examples for total twenty-one categories. Hereafter, all of the participants were required to select the most appropriate of three keywords for each category from the keyword lists. The result was shown as follows.

<Table 3> and <Table 4> showed the extracted keywords by five participants according to the individual information cognitive processing. We summarized all of the keywords that five participants emphasized the most representative keywords for each

<Table 3> Extracted Keywords by Individual Information Cognitive Processing _ Part 1

| Primary Category | Summary for Extracted Keywords by Individual Information Cognitive Processing |
|---|---|
| Books | book, story, read, bible, bookmark, library |
| Business | PDF, job, work, email, document, business, |
| Education | learn, student, education, kids, skill, language, question |
| Entertainment | TV, show, movie, watch, video, fun |
| Finance | account, money, bank, credit, finance, transaction, balance, payment, bill |
| Food & Drink | recipes, food, order, restaurant, meal, menu, cook |
| Health & Fitness | fitness, health, weight, training, exercise, running, tracker, sleep |
| Lifestyle | home, friend, photo, life, love, family, wallpaper |
| Medical | medical, care, doctor, blood, health, drug, pressure, patient, treatment |
| Music | music, song, iTunes, audio, playlist, artist, radio, listen |

<Table 4> Extracted Keywords by Individual Information Cognitive Processing _ Part 2

| Primary Category | Summary for Extracted Keywords |
|---|---|
| Navigation | map, GPS, location, route, parking, traffic, find, direction |
| News | story, news, subscription, weather, article, information |
| Photo & Video | photo, video, inteagram, camera, image, friend |
| Productivity | note, email, automatic, VPN, cloud, google, iPhone, iPad |
| Reference | translation, dictionary, English, search |
| Shopping | shopping, product, store, deal, itmes, coupons, brand, card, buy |
| Social Networking | friend, people, calls, chat, message, instagram, twitter, Facebook, dating |
| Sports | live, news, sports, game, team, league, player, ball, golf |
| Travel | travel, flight, information, trip, booking, hotel, location, tickets, airport |
| Utility | phone, device, call, Wi-Fi, email, QR, battery |
| Weather | weather, radar, forecast, location, temperature, satellite, warning |

category. The inter-rater reliability with Fleiss' Kappa=0.783 (P-value=0.000, standard error=0.014) for five participants showed a substantial agreement for the keywords extraction process.

We revisited the relevant data of previous study and reordered the extracted functionality keywords data from all of the category lists. A further verification process was performed in order to check the feasibility of adopting individual information cognitive processing as criteria or principles to classify apps on Apple iTunes Store. By setting new method in this study as a benchmark, <Table 4 and 5> shows the similarities and differences of extracted keywords from both of two methods. By reordering the keywords selected by five participants, the top three popular keywords were identified. Moreover, we compared the agreement of two methods by using inter-rater reliability statistics. The Cohen Kappa with 0.880 (P-value=0.000, standard error=0.118) showed almost perfect agreement between two methods.

By comparing our extracted results by individual information cognitive processing with prior study results by mixed method, both of two methods can extract similar top three representative functionality keywords for each category on Apple iTunes Store. Based on

<Table 5> Similarities & Differences of Extracted Keywords between Two methods _ Part 1

| Primary Category | Extracted Keywords by Two Approaches | |
|---|---|---|
| | Similarities | Differences |
| Books | book, read, story | bible, bookmark, library |
| Business | business, job, work | PDF, email, document |
| Education | learn, kids, student | skill, language, question, education |
| Entertainment | TV, movie, show | watch, fun, video |
| Finance | account, money, bank | credit, finance, transaction, balance, payment, bill |
| Food & Drink | food, meal, restaurant | recipes, order, menu, cook |
| Health & Fitness | fitness, weight, health | training, exercise, running, tracker, sleep |
| Lifestyle | life, home | **apartment**, friend, photo, love, family, wallpaper |
| Medical | medical, health, drug | care, doctor, blood, pressure, patient, treatment |
| Music | music, song, radio | iTunes, audio, playlist, artist, listen |

<Table 6> Similarities & Differences of Extracted Keywords between Two methods _ Part 2

| Primary Category | Extracted Keywords by Two Approaches | |
|---|---|---|
| | Similarities | Differences |
| Navigation | map, GPS, location | route, parking, traffic, find, direction |
| News | news, subscription | **live**, story, weather, article, information |
| Photo & Video | photo, video, camera | inteagram, image, friend |
| Productivity | automatic, note, device | device, email, VPN, cloud, google, iPhone, iPad |
| Reference | translate, dictionary | bible, English, search |
| Shopping | shopping, product, store | deal, itmes, coupons, brand, card, buy |
| Social Networking | friend, message, chat | people, calls, instagram, twitter, Facebook, dating |
| Sports | sport, ball, league | live, news, game, team, player, golf |
| Travel | travel, trip, hotel | flight, information, booking, location, tickets, airport |
| Utility | device, call, | support, phone, Wi-Fi, email, QR, battery |
| Weather | weather, temperature, forecast | radar, location, satellite, warning |

individual information cognitive processing, some keywords cannot be confirmed as the representative functionality keywords for relative categories, such as “apartment” for “Lifestyle Category”, “live” for “News Category”, “Bible” for “Reference Category”, and “Support” for “Utility Category”. Moreover, in the “Difference” column, those keywords extracted by individual information cognitive processing showed more representative meaning for different categories than the prior study approach.

# Ⅴ. Discussion

## 5.1 Discussion for Original Categorization on Apple iTunes Store

In both of the data collection process and categorization teaching and learning processes, all of the participants and researchers in this study could obviously perceive and discover the existed problems about the current categorization on Apple iTunes Store. Especially, in the categorization teaching and learning process, both of the lecturer and participants were very confused about some primary categories, such as productivity, utility, reference, and business. In terms of their category names and category descriptions, all of those categories contained somewhat abstract significances or meanings and the scope of each category itself is too wide. Another problem that could be easily perceived or observed was the classification for some multi-function, multi-meaning, and multi-attribution apps. For example, a lot of food-related apps have multi-functions of displaying recipes or restaurant information, locating the nearby restaurants, and placing orders online. Some apps may emphasize the online order settlement, but some apps may focus on displaying recipes or restaurant information. It may be confused for app developers to assign only one category for those apps. Therefore, establishing secondary category with more specific descriptions and keywords may be useful to classify those multi-functional apps. For some primary categories, such as medical category and health and fitness category, many relevant apps have similar main features. According to more specific observation and analyzing for those apps within two categories, it would be a better way to combine the two primary categories into one primary category with several secondary categories.

Based on the results of this paper, after all of those participants finished the cognitive teaching and learning process, they could use those extracted keywords to locate and classify new apps into appropriate categories. We performed several rounds of simple test by randomly selecting some new apps and asking all of five participants to classify. Basically, all of those new apps could be classified into more suitable categories. It also proved the feasibility of adopting individual information cognitive processing as a useful and available classification method to classify mobile apps.

### 5.2 Discussion for Keywords Extraction with Individual Information Cognitive Processing

According to the Basic Information Processing Model and the Store Model showed in <Figure 1 and 2>, five participants were invited to attend the individual information cognitive processing consisted of categorization teaching process and categorization learning process. Two participants are college students who have at least more than three years smartphone using experience. Another three participants who have several years smartphone using experience are randomly selected from surrounding population. During the categorization teaching process, five participants were interested in this project, and all of them showed actively attitudes for discussing and learning new knowledge. We have also provided enough cases and materials to help participants understand and apply relevant knowledge. All of the participants have been required to attend the meetings twice a week lasting for one month. Before they started to select and extract keywords from the keyword lists, all of them were familiar with the categorization as well as some relevant background information. For each category, the top three frequency of keywords were selected and we summarized all of the results from five participant's selection. All of this selecting process was proceeded separately and no external interference factors. Participant has full freedom to select the most appropriate keywords. The agreement among five participants for keyword extraction process was substantial agreement, which showed the reliability and accuracy of the extracted keywords. However, due to the differences in individual's knowledge background, cognitive level, and learning ability, the extracted keywords were different. But overall, the extracted keywords could accurately reflect the characteristics represented by each group.

For some categories as we have discussed before, such as business, reference, productivity, utility, etc., their category names, descriptions, and examples contained abstract significances that may caused inappropriate categorization. Some extracted keywords for different categories were also found to be similar or same with each other, such as "story" for News category and Books category, "photo" for Utility category and Photo & Video category, "weather" for News category and Weather category, "email" for Business category, Productivity category, and Utility category, etc. The too wide scope of those categories we mentioned before was also another reason for such problem.

The further comparative analysis showed the similarities and differences between regular keywords extraction method in prior research and the new keywords extraction method by adopting individual information cognitive processing. We revisited the relevant data of previous study and reordered the keywords frequency data from all of the category lists. <Table 4> shows the similarities and differences of extracted keywords between two methods. Some keywords in the top three results of prior study cannot be observed in the new method of this study, such as "apartment" in Lifestyle category, "live" in News category, "bible" in Reference category, and "support" in Utility category. By using individual information cognitive processing, participants ignored those keywords because more appropriate and more important keywords could be observed. Furthermore, those keywords may not faithfully reflect the characteristics of relevant categories. By performing a statistical measurement, the value of Cohen kappa showed a substantial agreement between two methods about the extracted keywords, which also proved the reliability and feasibility of adopting individual information cognitive processing as criteria for app store's categorization. From a cognitive psychology perspective, due to the difference of external objective conditions and internal subjective factors, although there are various differences between individuals, by setting up principles that are consistent with the information cognitive processing, individuals can apply those principles to practical application through a period of learning and training. Especially, when individuals have short-term memory or long-term memory about the principles as well as relevant responses, they can analyze new information in a more appropriate way. In this study, by teaching and learning the relevant information about categorization, individual's information cognitive processing can be considered as reliable methods to establish better categorization for app stores.

## Ⅵ. Conclusion and Future Research

The purpose of this study focused on adopting individual information cognitive processing as the classification criteria to update the current categorization on Apple iTunes Store. Furthermore, the effectiveness of the new criteria should be observed to identify whether the new research approach can have a feasibility to be used for classifying mobile apps into more appropriate categories. Total 4905 mobile app's specifics were scraped and analyzed. By using machine learning techniques, TF-IDF and SVD were performed in Python 2.7 programming environment and keywords lists for twenty-one categories were extracted. Based on Basic Information Processing Model and the Store Model, a research approach consisted of eight steps for categorization teaching and learning processes was conducted. The prior car app classification guideline was revisited and all of the relevant information was applied into individual information cognitive processing as reference for participant's learning and training processes. All of the five participants attended eight meetings in a month and then they were required to understand the categorization description on Apple Developer website and select representative keywords for each of twenty-one categories from the extracted keyword lists. The result of Fleiss' Kappa with 0.86 showed that five participants had enough individual information cognitive processing abilities about categorization on Apple iTunes Store. By comparing the similarities and differences between regular keywords extraction methods in prior study and new keywords extraction methods with individual information cognitive processing, it could be concluded that adopting individual information cognitive processing as criteria for categorization on app stores was proved to be reliable and feasible. The further inter-rater reliability with Cohen Kappa for two methods verified the conclusion.

This paper conducted a mixed research method consisted of machine learning techniques and cognitive psychology methods to verify the feasibility of adopting individual information cognitive processing as criteria of categorization on app stores. It may provide a new perspective for researchers, app developers, and app store hosts to improve and update the current categorization principles. Furthermore, by adopting individual information cognitive processing, researchers may have a better perspective to analyze the categorization problems and discover the solutions to relevant problems. This paper also provided some useful suggestions to update current categorization criteria for Apple iTunes Store.

In our future research, we are going to develop and improve the individual information cognitive processing in order to have more accurate results. Moreover, for those categories with abstract significances, we will try to segment those categories and establish more appropriate classification structures.

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<Abstract>

# A Feasibility Study on Adopting Individual Information Cognitive Processing as Criteria of Categorization on Apple iTunes Store

Zhang, Chao · Wan, Lili

**Purpose**

More than 7.6 million mobile apps could be approved on both Apple iTunes Store and Google Play. For managing those existed Apps, Apple Inc. established twenty-four primary categories, as well as Google Play had thirty-three primary categories. However, all of their categorizations have appeared more and more problems in managing and classifying numerous apps, such as app miscategorized, cross-attribution problems, lack of categorization keywords index, etc. The purpose of this study focused on introducing individual information cognitive processing as the classification criteria to update the current categorization on Apple iTunes Store. Meanwhile, we tried to observe the effectiveness of the new criteria from a classification process on Apple iTunes Store.

**Design/Methodology/Approach**

A research approach with four research stages were performed and a series of mixed methods was developed to identify the feasibility of adopting individual information cognitive processing as categorization criteria. By using machine-learning techniques with Term Frequency-Inverse Document Frequency and Singular Value Decomposition, keyword lists were extracted. By using the prior research results related to car app's categorization, we developed individual information cognitive processing. Further keywords extracting process from the extracted keyword lists was performed.

**Findings**

By TF-IDF and SVD, keyword lists from more than five thousand apps were extracted. Furthermore, we developed individual information cognitive processing that included a categorization teaching process and learning process. Three top three keywords for each category were extracted. By comparing the extracted results with prior studies, the inter-rater reliability for two different methods shows significant reliable, which proved the individual information cognitive processing to be reliable as criteria of categorization on Apple iTunes Store. The updating suggestions for Apple iTunes Store were discussed in this paper and the results of this paper may be useful for app store hosts to improve the current categorizations on app stores as well as increasing the efficiency of app discovering and locating process for both app developers and users.

***Keyword***: App Categorization, Individual Information Cognitive Processing, Latent Semantic Analysis, Inter-Rater Reliability, TF-IDF, SVD, Machine Learning

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