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非營利組織對關鍵字廣告之運用：
開放文化基金會個案研究

Keyword Advertising for Nonprofit Organizations:
A Case Study of Open Culture Foundation

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A Case Study of Open Culture Foundation

本論文係周韋綺君（R04749005）在國立臺灣大學企業管理碩士專班完成之碩士學位論文，於民國 107 年 1 月 12 日承下列考試委員審查通過及口試及格，特此證明

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中文摘要

本論文旨在探究非營利組織對於關鍵字廣告之運用，並以開放文化基金會作為個案研究之對象。小型非營利組織投入行銷時，常面臨財務困境及人力短缺，因此必須善用資源以最大化行銷效果。本論文聚焦於數位行銷下的關鍵字廣告，研究目的在於找出不同行銷標的下，能發揮最大效能的特定關鍵字屬性，以幫助非營利組織有效地選擇購買關鍵字，達到更佳的關鍵字廣告成效。

進行個案研究的資料分析時，我們根據 AARRR 模型的五個階段，提出對應的行銷目標，並採用迴歸分析辨別各項關鍵字屬性與這些標的之間是否相關、相關方向及相關強度。研究結果呈現不同關鍵字屬性在各階段的影響能力，我們嘗試解讀原因，討論後續應用及改善機會，綜整並提出關鍵字廣告運用之建議。

關鍵字：非營利組織、關鍵字廣告、迴歸分析、AARRR 模型、開放文化基金會

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Abstract

The purpose of this thesis is to uncover the possibilities for nonprofit organizations (NPOs) to better utilize the limited resource and optimize their online marketing effectiveness. Focusing on keyword advertising, our analysis aims to identify the significant factors and find out the specific attributes of the keywords that can affect advertising performance, and accordingly put forward the suggestions.

We conducted the case study on Open Culture Foundation (OCF), a Taiwan-based NPO. Performing the regression analysis of keyword attributes in the AARRR model, we examined and interpreted the relationships between independent variables (keyword attributes) and the dependent variable (advertising effectiveness measurement). Our research findings discover each attribute's potential impacts in particular stages.

Keywords: Nonprofit Organization, Keyword Advertising, Regression Analysis, AARRR Model, Open Culture Foundation

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Chapter 1

Introduction

A nonprofit organization (NPO) is an organization which is not conducted or maintained for the purpose of making a profit (Merriam-Webster, 2017). Many small NPOs share the common struggle of funding and manpower shortage. In the era of online marketing, although more advertising opportunities and low-cost promotion methods are available, how to best utilize the limited resource and optimize the marketing effectiveness still remains a crucial topic.

According to (Liquidreach, 2014), the average NPO marketing budget is 3% of the total revenue – in the for-profit world it is 10%. The Content Marketing Institution (CMI) and Blackbaud also reveal that most NPOs regard the lack of budget is the greatest challenge in marketing, and despite the various online approaches, the advertising method most used by NPOs is print or other offline promotion (CMI & Blackbaud, 2015).

Given the findings above, we learned that many NPOs have not fully taken advantage from the resource and the capabilities of online advertising methods, and when it comes to marketing, budget is their biggest concern.

The report from Interactive Advertising Bureau (IAB) shows that Internet advertising revenues in the United States totaled $72.5 billion for the full year of 2016, which increased 21.8% from the $59.6 billion reported in 2015 (PwC & Interactive

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Advertising Bureau, 2017). The figures reflect the fast-growing trend of marketers' interest, trust, and tendency to online advertising. Looking beneath the surface, it is Google that leads the revenue in this industry. Google is the largest recipient of global advertising revenue, and the advertising spending is consolidating as well (Molla, 2017) (eMarketer, 2017). The keyword advertising service by Google – AdWords[1], is highly discussed nowadays and is recommended by many experts for the advantages such as cost-efficiency, targeted traffic, transparent and instant data reported (Chris, 2015). It is important for NPOs to acknowledge the fact and keep up with the trend.

Table 1: Net US digital advertising revenues in top 5 companies (Billions)

	2016	**2017 (e)**	**2018 (f)**	**2019 (f)**
Google	\$29.43	\$35.00	\$40.08	\$45.69
Facebook	\$12.37	\$17.37	\$21.57	\$25.56
Microsoft	\$3.34	\$3.60	\$3.84	\$4.04
Oath	\$1.27	\$3.60	\$3.69	\$3.77
Amazon	\$1.12	\$1.65	\$2.35	\$3.19

Note. Data is reported by eMarketer (eMarketer, 2017). Retrieved November 28, 2017

[1] AdWords is an advertising service by Google. Advertisements can be displayed on Google and its advertising network. See https://www.google.com/AdWords/ Retrieved September 10, 2017.

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Since many small NPOs are suffering from the limited budget, they need to strive to seize every opportunity and resource. There are plenty of grant programs, subsidies, and various kinds of resource that NPOs could apply for and utilize. One of the biggest opportunities is Google Ad Grants[2].

Google Ad Grants is a program that provide free in-kind advertising to eligible NPOs. The eligibility requirement varies from country to country, but the common criterion is that the organization should be validated as a charitable organization. After the application is approved, the organization can receive $10,000 USD in-kind Google AdWords advertising each month. There are some rules and limitations, such as entirely text-based advertisement only (no videos or images), and the maximum cost-per-click (CPC) is fixed at $2.00 USD.

There are some successful stories shared by the adopters of the Google Ad Grants program. Science Buddies[3], an US-based educational organization joined the program in 2003, garnered 171,000 unique visits to their website in 2004, later increased to 773,000 by 2005, and the number doubled by 2006. Kiwis for kiwi[4], aiming to protect kiwi and their natural habitat in New Zealand, once frustrated by the plateauing web traffic, has reported their national fundraising traffic increased by 105% and reached an all-time high of 12,000 visitors after joining the program. Barnardos[5], one of Ireland's

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[2] https://www.google.com/grants/ Retrieved September 10, 2017.

[3] The sharing is posted on "Success Stories" by Google Ad Grants. https://www.google.com/grants/success-stories/science-buddies.html/ Retrieved December 9, 2017.

[4] https://www.google.com/grants/success-stories/kiwis-for-kiwi.html/ Retrieved December 9, 2017

[5] https://www.google.com/grants/success-stories/barnardos.html/ Retrieved December 9, 2017

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leading children charities, claimed their AdWords reached a record 9.5% conversion rate and outperformed their other online platforms; also, their AdWords currently drive 15% of all email registrations and 17% of all online donation (Google Ad Grants, 2017).

The adoption of online marketing is inevitable. Among the approaches available, Google's keyword advertising service is one of the most prominent methods that is widely used by marketers globally and is proven of the effectiveness. Moreover, with the advent of Google Ad Grants program, NPOs are now provided with considerable benefits in conducting their AdWords advertising.

This study is motivated by current challenges that NPOs faced, and we wish to answer the following questions:

1. How can NPOs utilize the resource and improve their keyword advertising?
2. How can NPOs identify the most effective keywords?
3. How does different keyword attribute influence the advertising performance? What kind of, in what aspect, and in what way?

The purpose of this thesis to understand how can small NPOs improve their online marketing performance by better making use of the resource and taking opportunities such as Google Ad Grants program. Take a step further and concentrate on keyword advertising, we wish to discover the solution to better manage and select the best profitable or effective keywords. Specifically, we would like to identify the significant factors and find out the particular attributes of the keywords that can affect advertising performance, and provide feasible, managerial recommendations for future decision-making on keyword investment.

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Considering that there are few studies solely focus on Taiwan-based NPOs and their marketing performances, we conducted a case study on one local organization who is currently a Google Ad Grants adopter, Open Culture Foundation (OCF), and its usage of keyword advertising.

We analyzed the empirical data by performing the regression analysis of keyword attributes in the AARRR model, which represents five phases of customer lifecycle and conversion behavior, to reveal different attribute's potential influences in each particular stage. The relationships between the independent variables (keyword attributes) and the dependent variable (advertising effectiveness measurement) are being examined and interpreted against common sense and known business best practices to uncover some insights into the special nature of NPO keyword advertising. Based on our research findings, we wish not only to provide suggestions and improvement plans for our subject of study, but also to contribute some insights and lessons-learned to other NPOs and individuals in this field.

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Chapter 2

Literature Review

In this chapter, we will first present the definition and the advantages of online marketing, and the different types of advertising that have been emerged under the influence of online marketing. Among the various of types of online advertising, we will then focus on keyword advertising. We will introduce the mechanism and summarize the common measurements used in the existing literatures, and present some challenges faced by the advertisers with respect to keyword selection. Since the purpose of this thesis is to reveal the online marketing improvement opportunities for NPOs, we will also present the researches which discuss the characteristics of NPOs and the studies about the adoption of online marketing by NPOs. Lastly, we will introduce the definition and the essences of the term “Growth Hacking”, of which we will conduct our empirical analysis based on one of the models built under this concept.

2.1 Online Marketing

2.1.1 Introduction of Online Marketing

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Online marketing has various alternative terms used by different researchers, such as Internet marketing or digital marketing. (Eley & Tilley, 2009) defines online marketing as the promotional activity on the Internet, including email marketing, search engine marketing, display advertising, social media marketing to name a few. According to (Chaffey, 2006), Internet marketing is an application of the Internet and related digital technologies in conjunction with traditional communications to achieve marketing objectives, and digital marketing shares the similar meaning, referring to the management and execution of marketing using electronic media as well as digital data about customer's characteristics and behavior.

There are many benefits and advantages of online marketing thanks to the ever-evolving Internet coupled with its unique capabilities. (Chaffey & Smith, 2005) suggests the advantage of online marketing includes growing sales by wider distribution and lower price, adding value by providing customers extra benefits online or information of product development through online dialogue and feedback, getting customer closer through website or emails, saving costs by reducing staff, post or postage costs, and extending the brand online. (Opreana & Vinerean, 2015) emphasizes on two features of online marketing, interactivity and engagement, which makes online marketing outshine the traditional approaches, because them allow marketers to have continuous conversations with customers in a more convenient and efficient way. (Edelmen, 2010) stresses the capability of gathering digital data and analyzing customer's decision journey in online marketing; by understanding the customer behavior can the marketers better allocate their efforts.

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2.1.2 Types of Advertising in Online Marketing

As many companies, organizations and individuals adopting online marketing, the advertising methods and forms are changing rapidly as well. (Belch & Belch, 2004) categorized the various online advertising approaches into six types: 1) *Keyword Advertising:* also known as keyword sponsor link or search-based advertising, the advertisements appear on webpages, which are targeted to match users' key search terms (keywords) queried on search engines. 2) *Banner:* the advertisement is an object on the webpage, containing text or graphics. 3) *Interstitial*: the advertisements show up while users are waiting for webpage loading. 4) *Pop-up*: the advertisements appear in its own window, when users open or close a webpage. 5) *Push*: using email or other technology to deliver messages to customers. 6) *Commercial Website*: the advertisements appear on the company's website. In addition to the types above, more and more forms of online advertising are emerging as the evolvement of Internet and technologies.

2.2 Keyword Advertising

2.2.1 Introduction of Keyword Advertising

The mechanism of keyword advertising is that the online advertisements will be placing on webpages, which are targeted to match key search terms (keywords) queried on search engines by users. Upon viewing the search results, users may click on the result that is most relevant to his or her needs, and then land on a website through the

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link embedded in the keyword advertisement. (Netzer, 2011) suggests there are three main players in keyword advertising: the advertisers, the search engines, and the customers (search engine users):

1. *Advertisers*: The advertisers can be companies, organizations, or individuals. In most keyword advertising services, an advertiser set the daily budget, determine the bid price for each keyword he or she selects, and designate advertisements associated with the keywords (Netzer, 2011).
2. *Search engines*: The search engines conduct certain mechanism to determine which advertisement to appear to match a user's query. Take Google for example, it analyzes three elements to calculate "Ad Rank", which decides where the advertisements are placed on the webpage or whether the advertisement will show at all; the three elements are bid amount, the components of the quality score (expected click-through rate, relevance, and landing page experience)[6], and the expected impact of extensions or formats (Hatch, 2015).
3. *Customers (search engine users)*: The search terms queried on search engines often reveal a customer's intention or buying interest at that moment. Customers are encouraged to click on the advertisement when it is tailored with high relevance to his or her immediate buying interest (Netzer, 2011).

A large number of studies have been conducted to measure the effectiveness or performances of keyword advertising. (Ghose & Yang, 2009) models click-through and conversion rates simultaneously, and also analyses the search engine's ranking decision

[6] See https://support.google.com/adwords/answer/7050591?hl=en&ref_topic=3122882/ for more details of the quality score. Retrieved December 1, 2017.

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and the advertiser's decision on CPC to conduct their empirical research. (Jerath, Ma, & Park, 2014) reveals the impact of keyword popularity on customer clicking behavior. The study compares the click-through and purchase behavior of two groups of customers: ones who search for the popular keywords (keywords with high search volume), and ones who search for less popular keywords. (Rutz & Bucklin, 2011) builds a model to capture and analyze the interplay between generic and branded keywords; the brand awareness affected by keyword advertising are also discussed. Customer-wise, (Blake, Nosko, & Tadelis, 2015) focuses on customer transactions, frequency, regency, and other demographic data when measuring the keyword advertising effectiveness. Attribution strategies and return on keyword investment is also one of the existing research foci in the field, which aims to attribute the real contribution and thus better measure the profitability and value of each keyword (Li, Kannan, Viswanathan, & Pani, 2016).

2.2.2 Challenges in Keyword Selection

The common challenge that advertisers face in keyword advertising is to find the right keywords and be able to buy enough of those. (Yang, Deng, Guo, & Ding, 2017) explains that as users can express their intention by typing a wide variety of different terms on search engines, it is difficult for an advertiser to find and bid on all the possible keywords; because of the limitation, most advertisers can only buy a handful of relevant keywords, which leads to insufficient advertising effect.

From advertiser's perspective, (Netzer, 2011) points out that given the limited budget, there is always a tradeoff between selecting too few profitable keywords, and

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not exhausting the entire daily budget, versus selecting too many keywords, and thus losing opportunities to receive clicks from profitable words that may arrive after the daily budget is exhausted. The dilemma remains a crucial issue for most marketers when facing keyword selection.

2.3 NPO's Marketing

2.3.1 Introduction of NPOs

The common characteristics of NPOs include mission-driven, resource constraints, and cater to multiple "publics", such as taxpayers, customers, donors, politicians (Yorke, 1984). NPOs are also defined as private, self-governing, not profit-distributing, and involves some meaningful degree of voluntary participation (Anheier, 2005).

Even though NPOs' goal is not to generate a financial profit, they still have to adopt the knowledge and skills similar to for-profit business. For instance, like for-profits, NPOs need to operate and develop strategies based on a understanding of their markets, customers, stakeholders, competitors (Rathi et al., 2016).

2.3.2 Adoption of Marketing by NPOs

NPOs' perception of marketing has been changing over the decades. In the past, marketing lagged dramatically in adoption by NPOs, compared to other functions (Kotler, 1979). Many NPOs disregarded the importance as well as misunderstood the purpose and approach of marketing (Bruce, 1995).

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Nowadays, because of the drastic digital usage surge and social media prevalence, NPOs are provided with numerous options of brand-new, cost-efficient marketing approaches. More and more NPOs are turning to the Internet to increase awareness, make promotions, deliver messages, and raise funds (Hart, 2002)

(McPherson, 2007) claims that a wide range of digital tools/platforms fosters the democratization in media and in philanthropy: people select issues and organizations' information for themselves; donors expect to have a say in the use of their money. It is necessary for NPOs to proactively interact and communicate, and provide various ways for people to get involved. (Ingenhoff & Koelling, 2009) uses content analysis on 134 NPOs to examine how they use website to create dialogic relationships with their stakeholder groups. Although not yet used efficiently by most NPOs, they seem to be acknowledging the importance of engaging publics (potential donors and media) via websites. For target audience and content marketing, (G. D. Saxton et al., 2007) conducts a research on 117 community foundations and the proportion of online content targeted at different stakeholder groups. It indicates they focus to deliver message to grant seekers and donors, and overlook community, media, employee/volunteer seekers, affiliates. (G. D. Saxton et al., 2007) also reveals NPOs' preference in technology to response and solicit feedbacks. The majority of survey subjects use "Contact Us / Ask a Question" button and Facebook; the rest methods include guestbook, message forum, online survey. As for measurement, a survey (J. Saxton, 2001) on 150 charity chief executives finds that the most popular measurement method for the use of the internet presence is hits, following by page impressions and unique visitors. Resource-wise, many small NPOs feel difficult to take full advantage of the online opportunities due to the lack of expertise, financial constraints, or limited access to some technologies (Pinho & Macedo, 2016).

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2.4 Growth Hacking

2.4.1 Introduction of Growth Hacking

The term of “Growth Hacking” or “Growth Hacker” is relatively young; the definition varies slightly when interpreted by different experts but still shares the similar concept. The term is first coined by Sean Ellis in 2010, referring to “a person whose true north is growth”; as “growth” is the most urgent and important thing for a startup. (Patel, 2015). (Ellis & Brown, 2017) put forward the statement that growth hacking focuses on acquiring customers, retaining them, engaging them and making them return repeatedly; it combines with product development, analytics and online marketing to achieve the goal of growth.

As (Peters, 2014) describes, a growth hacker is a hybrid of a technical genius and a marketer; they regard marketing as a fundamental aspect of how a product or service is designed and built. To emphasizes the mindset of favoring data, (Guz, 2016) calls growth hackers as quantifiers, who know the customer base by the numbers and use appropriate metrics to measure. Approach-wise, (Holiday, 2013) points out that growth hacking replaces the traditional marketing methods with only what is testable, trackable, and scalable. (Holiday, 2014) also claims that growth hacking believes the best decision a company can make is to have a product or service that fulfills the real and compelling needs for a real and defined group of people by continuous tests and refining, which echoes the concept of product market fit.

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2.4.2 AARRR Model

One of the exemplary reference for growth hackers is the AARRR model (Vunk, 2017). The AARRR model was first introduced in the talk of “Product Marketing for Pirate: AARRR! (aka Startup Metrics for Internet Marketing & Product Management)” at the Supernova conference by Dave McClure (McClure, 2007). The model aims to help startups understand the customer behaviors and find out the bottleneck or potential improvements. AARRR represents five stages of customer lifecycle and conversion behavior, which are acquisition, activation, retention, revenue, and referral:

1. *Acquisition*: In this stage, the ultimate goal is to identify where or what channels bring the users to our website. Furthermore, the relationship between channels and user behavior can be analyzed.
2. *Activatio*n: In this stage, we should understand user experiences when landing on the website, such as, how many pages do they view? How long do they stay? How many and what kind of interactions do they make?
3. *Retention*: In this stage, we should focus on the returning visitors. In addition to keeping acquiring new customers, it is also important to retain them.
4. *Revenue*: In this stage, we should analyze user’s conversion behaviors, which could be monetization behavior, like making a purchase or donation, or it could be non-monetizating, such as the actions of download or subscribe.
5. *Referral*: In this stage, the benefit of networking effect in marketing is emphasized. Especially under the prevalence of social media nowadays, the influence that referrals can make is even more powerful.

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Chapter 3

Methodology

3.1 Case Study

According to (Yin, 1994), among various research methods, case study is the preferred strategy when “how” or “why” questions are proposed, when the researchers has little control over the events, and when the focus is on a contemporary phenomenon within some real-life context.

(Eisenhardt, 1989) claims that case study approach is suggested in new topic areas, and the resultant is often novel, testable, and empirical valid. To be more specific, case study strategy’s independence from prior literature or past empirical observation makes it particularly appropriate for new research areas or research areas for which existing relative inadequate theory.

As mentioned in *Chapter 1*, there are few studies solely focus on Taiwan-based NPOs and their online marketing performances. Secondly, we put forward our research questions on how can NPOs utilize the resource and improve their keyword advertising, how can they identify the most effective keywords, and how does different key attribute influence the advertising performances. Furthermore, the increasing prevalence of keyword advertising is undoubtedly a contemporary phenomenon and it is closely

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interplaying with people's daily life and behaviors. Given the reasons above, we believe the case study method is best appropriate for this thesis.

3.2 Regression Model

The general purpose of regression model is to understand the relationship between several independent variables and a dependent variable. The dependent variable is the variable being tested or measured, while the independent variables are changed or controlled to observe the effect on the dependent variable. The model is presented as the following:

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_n x_{in} + \epsilon_i$$

Where *y* is the dependent variable, x_{ij} is the j-th independent variable, and there are *n* independent variables.

Since our research goal is to find out the potential impact of different keyword attributes on the advertising performance, we are convinced that regression model is well-suited for our data analysis. We choose the measurement commonly used in keyword advertising evaluation as the dependent variable, such as clicks or conversions, and we design a set of independent variables which represent the keyword attributes. The variable selection will be shown in details in the next chapter.

We use the R programming language's linear and logistic regression functions to perform the calculation. For linear regression, the lm() function in R uses the linear least squares design from (Chambers, 1992). The glm() function used for logistic regressions uses iteratively reweighted least squares algorithm from (Hastie & Pregibon, 1992).

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After the coefficients are fitted to the research data, we look for ones with small p-values, which indicates strong statistical relationship between the independent variables and the dependent variable. These relationships are then carefully examined against common sense and known business best practices to uncover some insight into the special nature of NPO keyword advertising.

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Chapter 4

Empirical Analysis

In this chapter, we will first introduce our case – Open Culture Foundation. The content covers the background of the organization, the website structure, and the donation project. Secondly, the research data will be presented in details, including data source, data format, data timeframe, and the data overview, that is, the overall online marketing performance in the given timeframe. Next, we will analyze the empirical data by conducting the regression analysis of keyword attributes in the AARRR model, which represents five phases of customer lifecycle and conversion behavior, to discover different attribute's potential influences in each particular stage.

We select 12 important attributes in five categories as our independent variables, which are 1) Keyword Essence: *foundation, open source, technology, government*; 2) Event Type: *computer science-related event, student summer/winter camp*; 3) Action Type: *call for donation, call for newsletter subscription*; 4) Device Category: *mobile traffic, tablet traffic*[7]; 5) Language: *Chinese, mixed language*[8]. For each stage of the AARRR model, we designate the commonly used advertising performance

[7] Device-wise, we choose "desktop traffic" as the reference level, and make "mobile traffic" and "tablet traffic" as indicator variables. Details of variables are elaborated in *Section 4.3.1*.

[8] "Chinese" and "mixed language" are indicator variables while "English" is the reference level.

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measurement as the dependent variable. 1) Acquisition stage: *Clicks*; 2) Activation stage: *Bounce rate*; 3) Retention stage: *Percentage of new sessions*; 4) Revenue stage: *Conversions*. However, the referral stage will be excluded from the research because we do not have any referral data related to Google AdWords keyword advertising. After examining the relationships between the independent variables (keyword attributes) and the dependent variable (advertising effectiveness measurement), we accordingly put forward our suggestions based on the findings and implications.

4.1 Open Culture Foundation

4.1.1 Organization Introduction

Open Culture Foundation (OCF) is a nonprofit organization pursues the awareness and usage of open source in a broad sense, founded in 2014 by several members of Taiwan's open source communities.

The concept of open source has been influencing many ideologies and movements with its ethos of access to the source, free remix and redistribution, end to predatory vendor lock-in, and higher degree of cooperation (Socailsquare, 2014). The term "source" was originally referred to source code in computing; however, the idea of open, transparent, accessible and participable source has been adopted in many fields, not limited to software and hardware engineering. For instance, the free sharing of skills and knowledge, the Creative Commons-licensed works, and the open documents of governments.

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Taiwan's open source communities have been highly active, and many events and conferences are held frequently by these communities. They usually also sell the events and conference tickets. Nevertheless, when it comes to handling the ticket's transactions and accounts, it is a big trouble for each community due to the lack of expertise in government regulations and each organization's own limitations. The idea of establishing a registered foundation[9] was thus ignited, and OCF was founded accordingly.

The original intention of OCF was to assist the local communities in handling administrative issues such as ticket sales transactions and receipts. On top of that, it greatly helps online advertising campaigns, and sometimes provide volunteers on-site. The main goal of OCF now has shifted to advocating the use of open source software/hardware and open data by supporting the open source communities.

On the other hand, in order to be self-sustained, OCF also launches donation campaigns to cover its own expenses, which were mostly spent on personnel costs. Individuals and organizations' donation is OCF's main income source.

4.1.2 Website Structure

There are five main sections on the website of OCF: About, People, Projects, Journal, and Media kit. There is a "Join Us" button on top of the homepage, which leads to the donation page (more details explained in *section 4.1.3*). An English version is

[9] According to Taiwan's Civil Code, the non-profit-seeking legitimate and registered public groups can be categorized under charitable corporations; foundation is one of the varied forms.

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available, yet not all contents are completed. The homepage screenshot and the website structure are shown in Figure 1 and Figure 2, respectively.

Note. From http://ocf.tw/ Retrieved September 10, 2017.

Figure 1: Screenshot of OCF homepage

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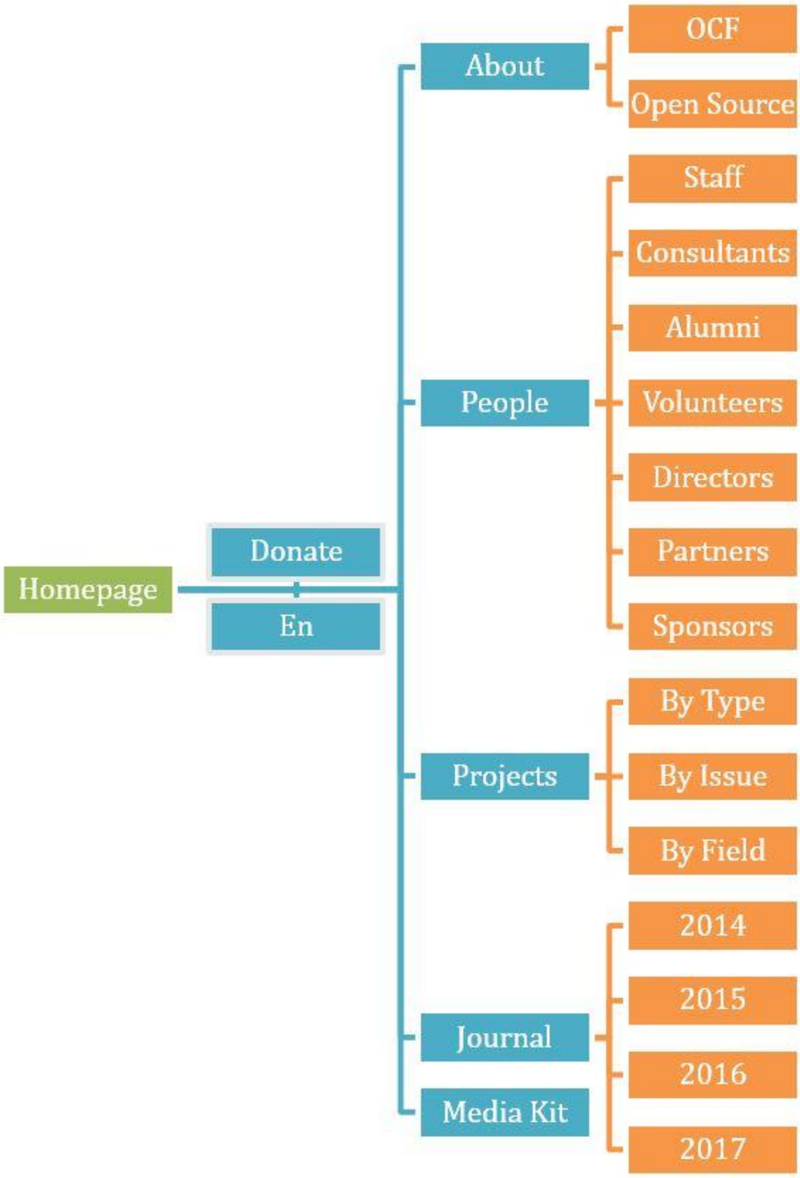

Figure 2: OCF website structure

4.1.3 Donation Project

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OCF initiated the Google AdWords campaign and later on joined Google Ad Grants program in March, 2015. On February 3rd 2016, OCF launched a long-term small donation project named "OCF 300 Warriors (OCF 開源 300 壯士)"[10]. It aims to call for donors to donate NTD 300 per month continuously. When a user reaches the donation page, he or she will read the descriptions, after filling out the online sheet and finishing the donation process, it will be recorded as one conversion in the Google Analytics report. Donors are free to terminate the donation, but the terminations are not reflected on the report.

The steps of conversion path are as follows:

Step 1: Understand how does the donation project works. OCF asks donors to donate NTD 300 per month, and the amount will be auto-paid by credit cards. Donors will receive an email each month after the transfer is done; donors can terminate the donations by contacting OCF. The default monthly payment is NTD 300, but donors are free to adjust the amount.

Step 2: Fill out the donation sheet. Donors will fill out the online sheet of payment setting (monthly amount) and personal information (name, email address, receipt info, ID number, etc.)

Step 3: Confirm the donation information.

[10] Starting from May 2016, there is an another project called "OCF x g0v Joint Donation (OCF 開源 300 壯士 x g0v 大松認養人)" . The joint project asks donors to donate NTD 600 per month; half of the amount will be donated to OCF, and half to g0v. In this thesis, the term "donation" denotes the "OCF 300 Warriors" project only.

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Step 4: Complete the donation. Donors will provide and submit the credit card information, and finish the donation process. Donors will be redirected to ECPay[11], the third party payment webpage (https://payment.ecpay.com.tw/Cashier/AioCheckOut) afterward. Then the conversion is recorded in Google Analytics.

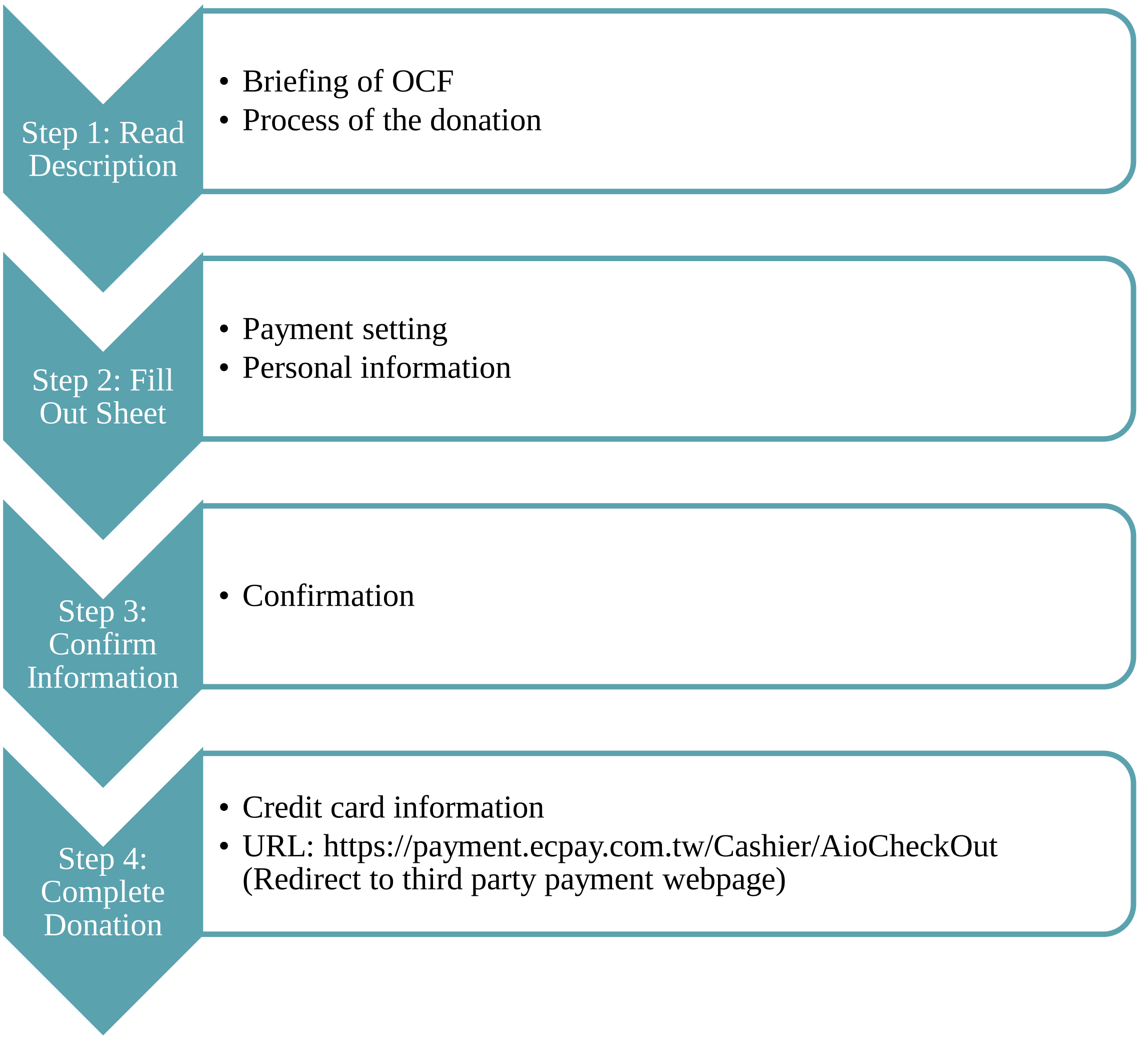

Figure 3: Conversion path

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[11] The payment service is provided by Green World FinTech Service Co. (綠界科技). See more service introduction on https://www.ecpay.com.tw/ Retrieved September 16, 2017.

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4.2 Research Data

4.2.1 Data Scope

OCF granted us with the access to its Google Analytics account with the "viewing and analysis" permission.

The basic reports in Google Analytics contains two data types: dimensions and metrics. Dimensions are attributes of the data while metrics are quantitative measurements. The dimensions and metrics we will use for our analysis are listed as follows:

Dimensions

1. **Channels:** There are five default channel categories in Google Analytics, indicating where does the acquisition come from. 1) *Paid Search*: Traffic that arrives through a paid search campaign like Google AdWords advertisements. 2) *Direct:* Traffic that arrives directly by typing the URL, clicking on the bookmark, etc. 3) *Organic Search:* Traffic that arrives through unpaid search like a non-paid Google Search result. 4) *Social:* Traffic that arrives through social media or social network like Facebook, Twitter, LinkedIn, etc. 5) *Referral:* Traffic that arrives after the user clicked on a website other than a search engine.
2. **Keywords:** OCF's Google AdWords and Google Analytics accounts are linked, hence the keywords bought in Google AdWords with at least one click (used by users to reach the website) being tracked will be shown in this

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dimension.

3. **Device Category:** There are three default categories, which are desktop, mobile, and tablet.

4. **User Type:** The two types are new (first-time) visitors and returning visitors.

Metrics

1. **Clicks:** The number of times users click on the advertisement.
2. **Sessions:** Total number of sessions within the date range. Session is a group of interactions one user takes within a given timeframe (30 minutes by default) on the website
3. **% New Sessions:** An estimated percentage of sessions created by the first-time visitors.
4. **New Users:** Total number of the first-time visitors.
5. **Bounce Rate:** The percentage of users to leave the website without any other interaction after viewing only one page.
6. **Avg. Session Duration:** The average length of a session, measured by seconds.
7. **Conversions (Goal Completions):** The total number of conversions to the goal. In OCF's case, the goal is a user to complete the donation process.

As for the timeframe, we wish to evaluate the performance of keyword advertising of OCF in the year of 2017. The study was conducted in September, so the data we analyzed was from January to August, 2017.

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4.2.2 Data Overview

In the timeframe of January to August 2017, OCF has accrued 32,268 sessions, acquired 25,199 new users, and reached 144 conversions. The average bounce rate is 75.15% and the average session duration is 79 seconds. The ratio of new users vs. returning users is 8:2. We will present the overview of marketing performance in the perspectives of cross-year comparison, cross-channel comparison, and seasonality analysis in the following sections.

4.2.2.1 Cross-Year Comparison

Compared to the same timeframe in the previous year, both acquisition and conversion decrease, while user behavior (bounce rate and average session duration) improves. The retention rate remains steady. The changes from 2016 to 2017 of marketing performance is shown in Table 2.

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Table 2: Changes from 2016 to 2017 (January – August) of marketing performance

Metric	2016	2017	Change	Indicator
Session	58,411	32,268	-45%	Decreasing
New User	45,765	25,199	-45%	Decreasing
Conversion	211	144	-32%	Decreasing
Bounce Rate	80.24%	75.15%	-6%	Improving
Session Duration (sec.)	55	79	44%	Improving
Ratio of New vs. Returning User	7.84 : 2.16	7.81 : 2.19	-0.4%	Stabilizing

4.2.2.2 Cross-Channel Comparison

For acquisition metrics, paid search channel contributes the most traffic and referral channel contributes the less. For adjusted[12] conversions, the direct channel contributes the most conversions, while the paid search channel contributes the less.

[12] The original conversion number is misleading due to some technical problems. The clarification and detailed adjustment are explained in *Section 4.3.5*.

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For user behavior metrics, paid search has the worst performance both in average bounce rate (the highest) and average session duration (the shortest). For retention data, paid search channel has the highest new-to-returning user ratio, while referral channel has the lowest.

An overall view of the best and the worst performing channels in each measurement is presented in Table 3. The numbers under those metrics are shown in the following tables and figures.

Table 3: Marketing performances overview by channel (January – August, 2017)

Metric	**Goal**	**Best Performance**	**Worst Performance**
Session	Higher	Paid Search	Referral
New User	Higher	Paid Search	Referral
Conversion	Higher	Direct	Paid Search
Bounce Rate	Lower	Organic	Paid Search
Session Duration	Longer	Referral	Paid Search
Ratio of New vs. Returning User	Lower	Referral	Paid Search

Note. In this discussion, we assume the lower the new-to-returning ratio the better.

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Table 4: Sessions in different channels (January – August, 2017)

Channel	**Sessions**	**Percentage**
Paid Search	13,398	42%
Direct	8,653	27%
Organic Search	4,769	15%
Social	4,003	12%
Referral	1,415	4%
Total	32,238	100%

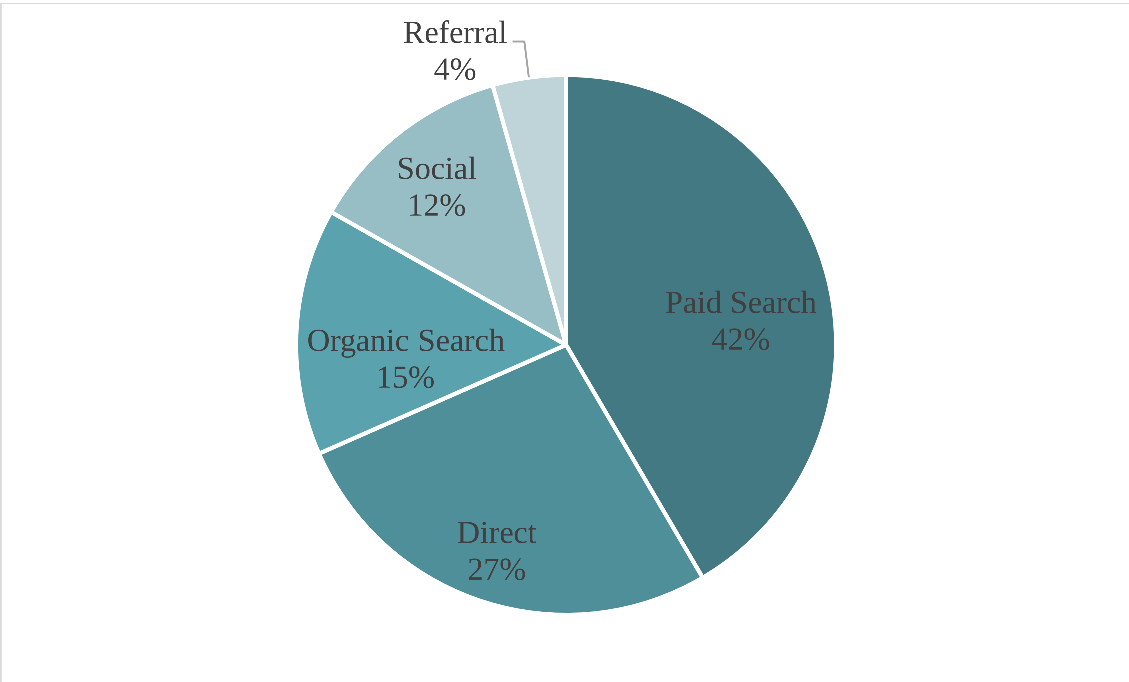

Figure 4: Percentage of sessions by channel (January – August, 2017)

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Table 5: New users in different channels (January – August, 2017)

Channel	New Users	Percentage
Paid Search	11,452	45%
Direct	7,106	28%
Organic Search	3,247	13%
Social	2,735	11%
Referral	677	3%
Total	25,217	100%

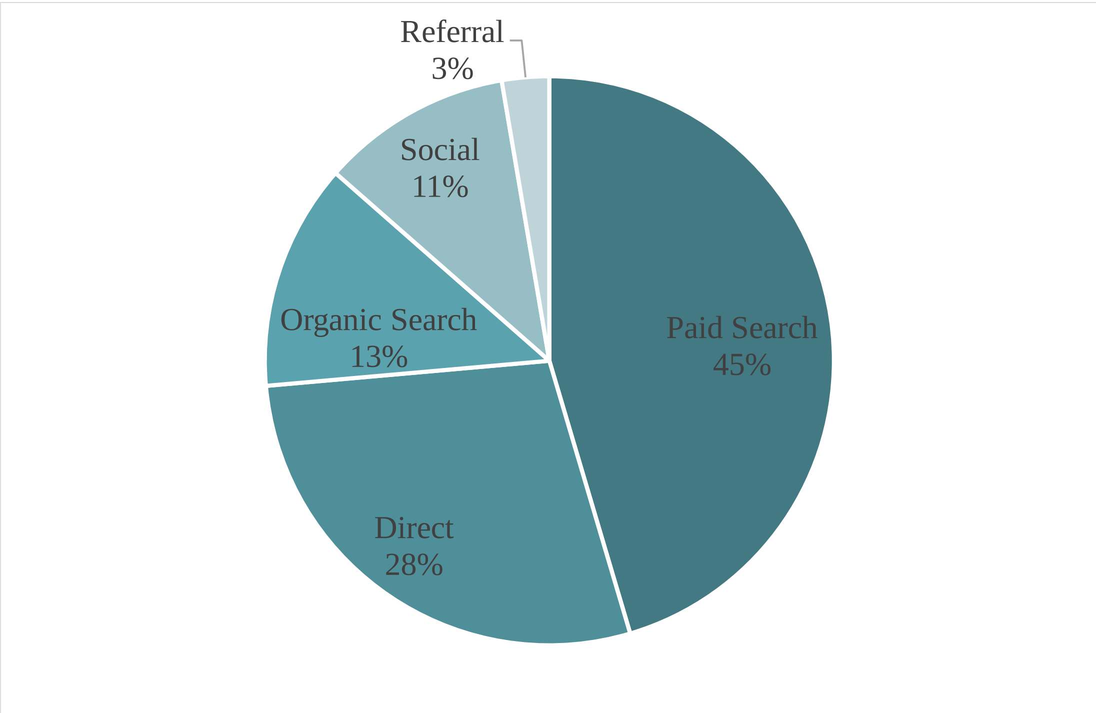

Figure 5: Percentage of new users by channel (January – August, 2017)

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Table 6: Adjusted conversions in different channels (January – August, 2017)

Channel	Adjusted Conversions	Percentage
Direct	65	45%
Social	42	29%
Referral	18	13%
Organic Search	18	13%
Paid Search	1	1%
Total	144	100%

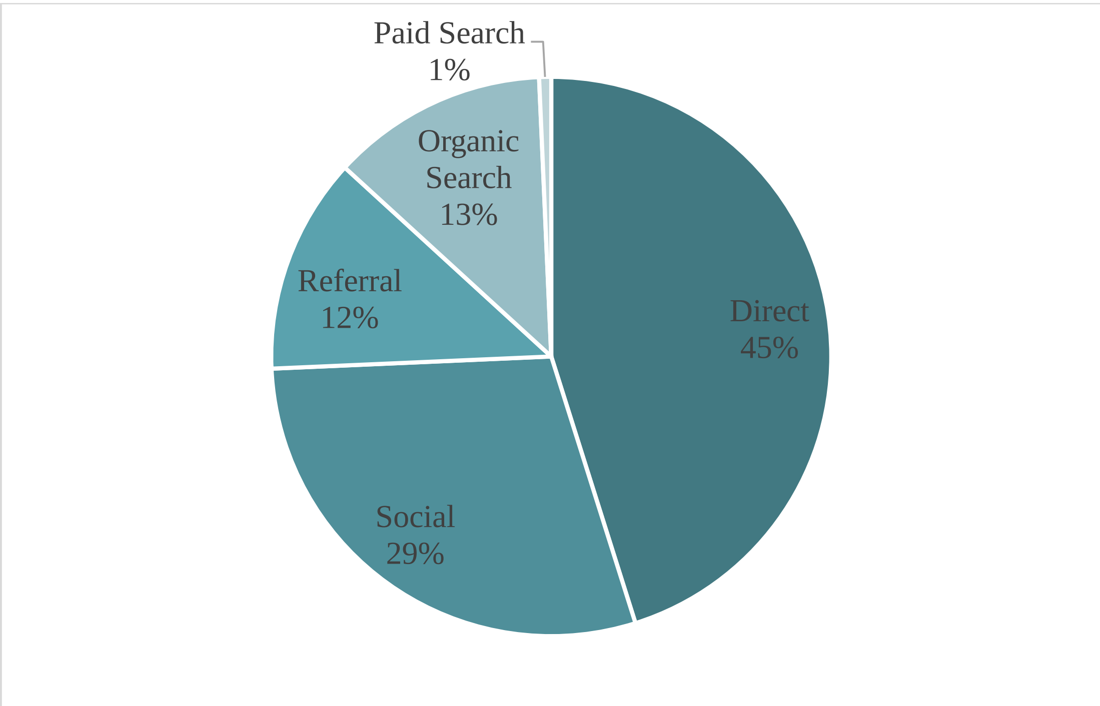

Figure 6: Percentage of adjusted conversions by channel (January – August, 2017)

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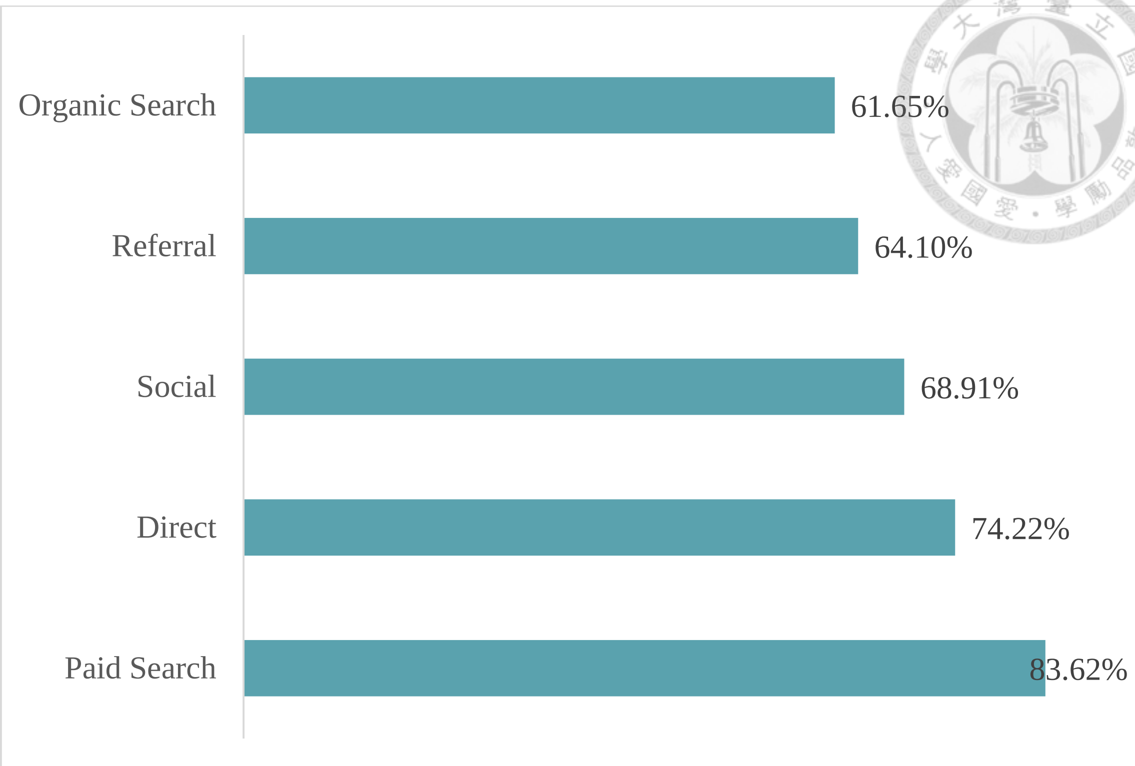

Figure 7: Bounce rate in different channels (January – August, 2017)

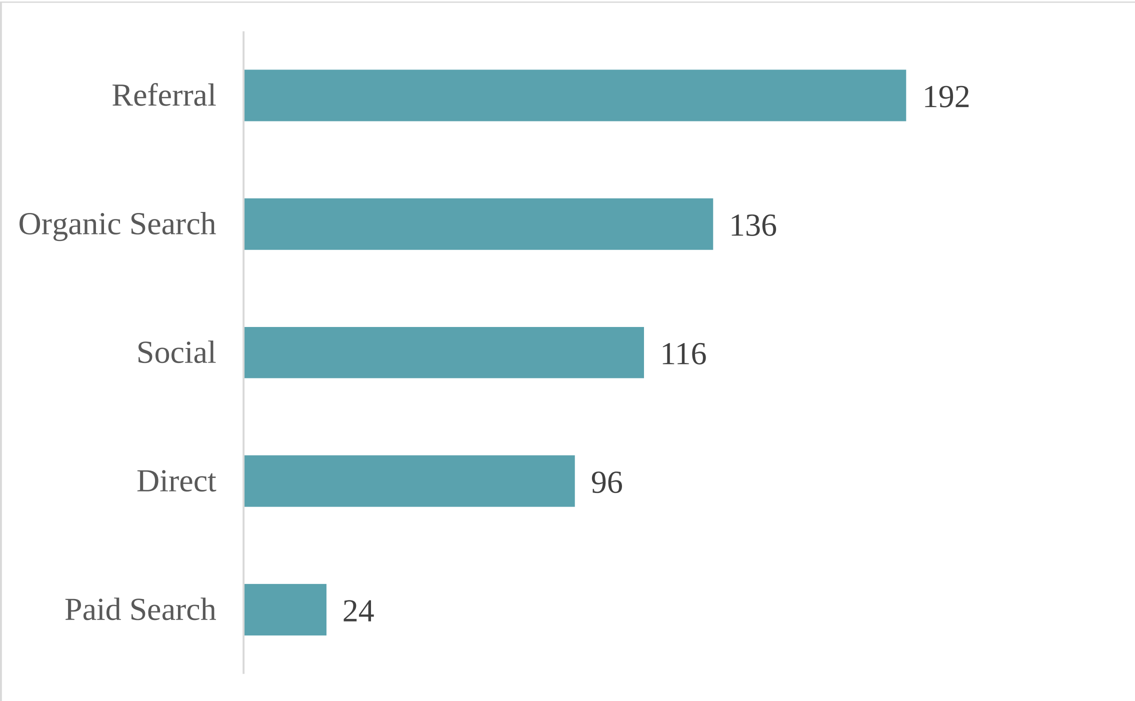

Figure 8: Session duration (seconds) in different channels (January – August, 2017)

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Table 7: Sessions generated by new and returning visitors (January – August, 2017)

Channel	New Visitors	Returning Visitors	Ratio of New vs. Returning
Paid Search	11,452	1,946	8.55 : 1.45
Direct	7,106	1,547	8.21 : 1.79
Organic Search	3,247	1,522	6.81 : 3.19
Social	2,735	1,298	6.78 : 3.22
Referral	677	738	4.78 : 5.22
Total	25,217	7,051	7.81 : 2.19

4.2.2.3 Seasonality

In terms of seasonality, the period of May to June has accumulated most sessions; and the peaks of conversion also happen in these two months.

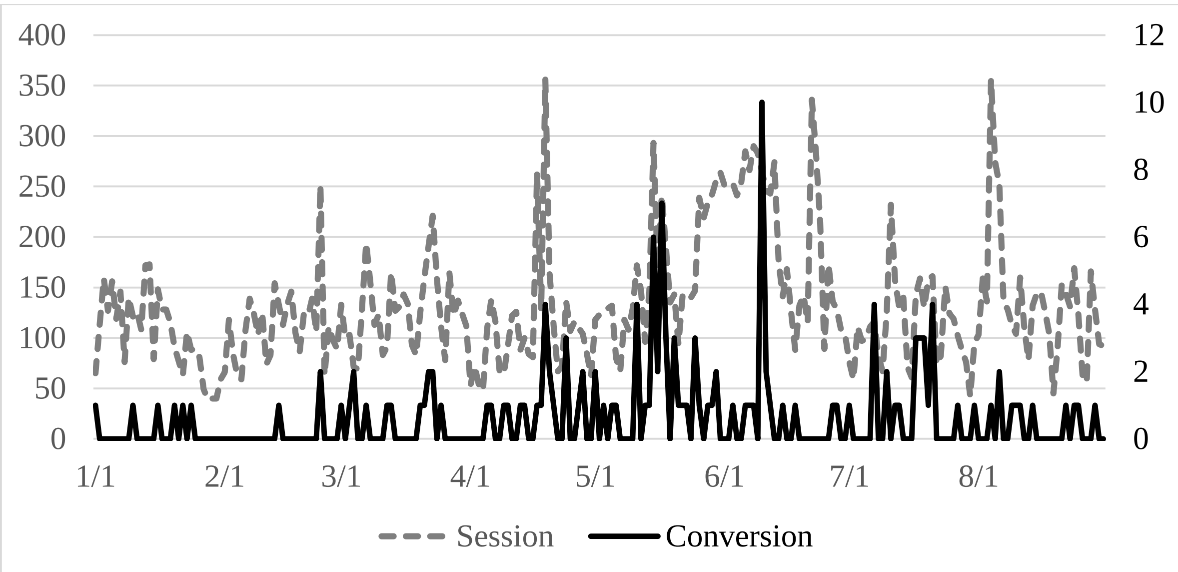

Figure 9: Timeline of sessions and conversions (January – August, 2017)

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4.3 Regression Analysis of Keyword Attributes in the AARRR Model

Our goal is to identify the significant factors or the specific attributes of the keywords that can affect advertising effectiveness in each stage of the AARRR model. However, we do not have any referral data related to Google AdWords keyword advertising; hence the referral stage will be excluded from our following discussion.

In each phase, we will first present the overview of OCF's keyword advertising. Then, we will reveal the relationships between the keywords' attributes and the advertising performances by using the regression analysis. Lastly we will make our suggestions based on the findings and the implications.

4.3.1 Sample and Variable

There are 278 keywords bought by OCF in the timeframe of January to August 2017. Each keyword can be reached by users via three different kinds of devices: desktop, mobile, and tablet. Taken the device difference into account, we have the total sample size of 580 keywords.

For the distinct perspectives of evaluation – acquisition, activation, retention, and revenue – we choose different dependent variable to better understand the effectiveness. However, to keep the comparison of keyword attributes among stages consistent, we use the same set of independent variables in each stage. We designate the attributes of "Essence", "Event type", "Action type", "Device category" and "Language" to put

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independent variables into five main categories; the variable IDs are shown in the parentheses.

I. Essence of the keyword

1. Foundation (foundation)

2. Open Source in a Broad Sense (opensource)

3. Technology (tech)

4. Government (gov)

OCF is a nonprofit foundation whose ultimate goal is to advocate the usage of open source. Therefore, the majority of its keywords are related to foundation and open source. Among the keywords, there are also many falling into the category of technology, that is, the keywords are about some specific programming languages, source codes, hardware and software, or online collaborative editors/platforms. Another type of keywords is government related. The free and accessible documents of public sectors, the movement of citizen participation, or the communities dedicated to governments' open data, etc.

II. Event type of the keyword

5. Computer Science Related (event_cs)

6. Student Summer/Winter Camp (event_camp)

Since one of the main function of OCF is to promote and assist the events held by the local communities, there are many activity keywords. Because of the nature of open source events, most of them are computer science related, for instance, hackathon, COSCUP (Conference for Open Source Coders, Users and Promoters), PyCon (Python

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Conference). Perhaps it is SITCON (Students' Information Technology Conference) that gives OCF the idea to buy student camp related keywords, there are also a considerable amount of keywords about children and student summer/winter camp.

III. Action type of the keyword

7. Donation (action_donation)

8. Newsletter Subscription (action_newsletter)

When it comes to call-to-action advertisement of OCF, there are two types: donation and newsletter subscription. Intuitively, this kind of keywords should have obvious difference from others, for example, higher conversion rate.

IV. Device category of the keyword

9. Mobile (device_mobile)

10. Tablet (device_tablet)

There are three device categories tracked in Google Analytics: desktop, mobile, and tablet. We choose desktop as the reference level, and make mobile and tablet as indicator variables. With the high smartphone user penetration in Taiwan, we wish to see whether there is, and how is the differences between desktop and mobile user behavior.

V. Language of the keyword

11. Chinese (language_ch)

12. Mixture of English and Chinese (language_mix)

There are three types of language: all Chinese characters (e.g. "開放政府"), all

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English characters (e.g. “g0v”), or mixture of both (e.g. “政府 open data”). We choose English as the reference level, and we wish to find out whether or not the language of keywords is an important factor.

We labeled each keywords with the attributes above, and the example is shown in Table 8. The total count of each attribute is shown in Table 9.

Table 8: Example of keywords attributes labeling

	基金會	**COSCUP**	**政府 open data**	**免費電子報**
foundation	1	0	0	0
opensource	0	1	1	0
tech	0	1	0	0
gov	0	0	1	0
event_cs	0	1	0	0
event_camp	0	0	0	0
action_donation	0	0	0	0
action_newsletter	0	0	0	1
device_mobile	0	1	1	0
device_tablet	0	0	0	0
language_ch	1	0	0	1
language_mix	0	0	1	0

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Table 9: Count and example of each independent variable

Variable	Count	Example
foundation	88	基金會, 基金會 徵才, 財團法人基金會, 基金會 贊助, open culture foundation
opensource	215	自由軟體, 開放資料, COSCUP, firefox, g0v
tech	210	程式競賽, 程式學習, linux, scratch, github
gov	28	公民記者證, 政府 資料 開放 平台, 萌典, g0v, open government data
event_cs	40	黑客松, 駭客松, COSCUP, PyCon, SITCON
event_camp	153	營隊, 大學夏令營, 高中夏令營, 電腦夏令營, 夏令營 推薦
action_donation	16	基金會 贊助, 贊助 基金會, 基金會 捐款, 小額捐款, 公益捐款
action_newsletter	28	電子報, 電子報訂閱, 免費電子報, 網路電子報, 電子報 推薦
device_mobile	223	基金會, 電子報, 營隊, COSCUP, firefox
device_tablet	90	基金會, 電子報, 營隊, COSCUP, firefox
language_ch	456	基金會, 電子報, 營隊, 自由軟體, 開放資料
language_mix	9	政府 open data, R 語言, python 教學, raspberry pi 樹梅派, ymca 暑期夏令營

Note. The total count exceeds the sample size because a keyword can have more than one attributes.

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To clarify, keywords with the same word strings can be reached by users from different devices and accordingly have different labeling, and are regarded as different keywords.

Table 10: Example of labeling for keywords with same word strings

	基金會	**基金會**	**基金會**
foundation	1	1	1
opensource	0	0	0
tech	0	0	0
gov	0	0	0
event_cs	0	0	0
event_camp	0	0	0
action_donation	0	0	0
action_newsletter	0	0	0
device_mobile	**1**	**0**	**0**
device_tablet	**0**	**1**	**0**
language_ch	1	1	1
language_mix	0	0	0

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Also, keywords with exact same meaning can be presented in Chinese, English, or mixture of both languages. Therefore, they have different labeling, and are regarded as different keywords.

Table 11: Example of labeling for keywords with same meaning

	政府開放資料	**government open data**	**政府 open data**
foundation	0	0	0
opensource	1	1	1
tech	0	0	0
gov	1	1	1
event_cs	0	0	0
event_camp	0	0	0
action_donation	0	0	0
action_newsletter	0	0	0
device_mobile	1	1	1
device_tablet	0	0	0
language_ch	**1**	**0**	**0**
language_mix	**0**	**0**	**1**

doi:10.6342/NTU201800083

The approach of variance inflation factors (VIF) is commonly used to identify collinearity among independent variables. A recommended maximum VIF value is 5 (Rogerson, 2001) or even 4 (Pan & Jackson, 2008). We use the vif() function in R to perform the calculation, and the outcomes show that all VIF values are below the desired threshold.

Table 12: Variance inflation factors values

	VIF
foundation	1.839480
opensource	2.988788
tech	2.572220
gov	1.517867
event_cs	1.048061
event_camp	2.365573
action_donation	1.098440
action_newsletter	1.312481
device_mobile	1.134302
device_tablet	1.161969
language_ch	1.860706
language_mix	1.113754

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4.3.2 Acquisition

4.3.2.1 Descriptive Statistics

How do visitors find OCF and arrived at the website? There are many ways: a user can find the website through a Google AdWords text ad, by scanning the QR code, or by clicking the shared link on his or her friend's tweet. According to Table 5, paid search (Google AdWords advertising) is the largest channel that contributes 11,452 new users, which accounts for 45% of the total.

In acquisition, we care about how users arrive on the OCF website. When clicking on an AdWords advertisement, a user will be redirected to the website. Therefore, we choose the total number of "clicks" for each keyword as the dependent variables.

There are total 20,279 clicks attributed from 580 keywords, with the average at 34.96 clicks per keyword. There is only one keyword, "基金會 (foundation)" in the device category of "desktop", that garners over 1,000 clicks. The rest of the keywords have clicks below 1,000, and the most of them fall into the groups of under 500 clicks.

Table 13: Clicks (January – August, 2017)

Average	**Std.**	**Min.**	**Q1**	**Medium**	**Q3**	**Max.**
34.96	105.20	1	2	5	21	1495

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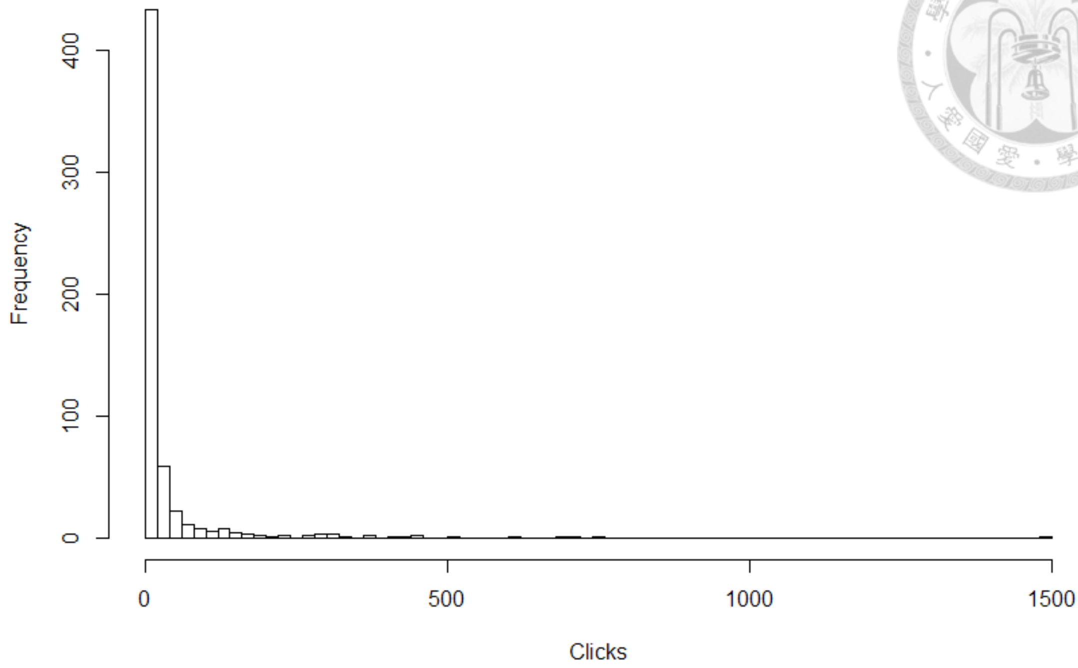

Figure 10: Histogram of clicks (January – August, 2017)

4.3.2.2 Regression Analysis

Among the 12 variables, we find five are significant (p-value < 0.05). The regression model is shown below:

$$Click_i = \beta_0 + \beta_1 foundation_i + \beta_2 opensource_i + \beta_3 tech_i + \beta_4 gov_i + \beta_5 event\_cs_i + \beta_6 event\_camp_i + \beta_7 action\_donation_i + \beta_8 action\_newsletter_i + \beta_9 device\_mobile_i + \beta_{10} device\_tablet_i + \beta_{11} language\_ch_i + \beta_{12} language\_mix_i + \epsilon_i$$

doi:10.6342/NTU201800083

Table 14: Summary of regression analysis (Dependent variable: *Click*)

Independent Variables	Coefficients	P-value	Significant codes
foundation	69.404	6.06E-06	***
opensource	20.049	0.17467	
tech	-7.967	0.55558	
gov	17.071	0.47336	
event_cs	54.994	0.00117	**
event_camp	-12.182	0.37133	
action_donation	-68.120	0.10487	
action_newsletter	51.257	0.04752	*
device_mobile	-20.085	0.02811	*
device_tablet	-58.093	3.67E-06	***
language_ch	5.593	0.68718	
language_mix	-2.014	0.95494	
		R^2	0.1067
		Adjusted R^2	0.08784

Note. Significant codes: *** p<0.001, ** p<0.01, * p<0.05, · p<0.1

4.3.2.3 Findings and Implications

In terms of keyword's essence, "foundation" has significant and positive influence

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to accrue clicks. There are 88 foundation-related keywords among the total sample size of 580. Since the result indicates the foundation-related keywords has positive impact on clicks, we suggest OCF to focus on finding and buying more keywords in this category. Open source-related keywords do not have a strong tendency to attract clicks, which contradicts our intuitive assumption since the core value of OCF is to advocate the usage of open source.

In the aspect of event, the computer science related activities have significance on influencing clicks. This is a great news for OCF because one of their main functions is to promote and assist the events held by local communities, and they should keep and reinforce the efforts on promoting events in Google AdWords. There are also many student camp related keywords in OCF's account; however, the performance is not as satisfying.

For the keywords with action purpose, ones call for donation do not have obvious influence, while ones call for newsletter subscription have positive and significant impact on clicks.

As for user device category, we choose desktop as the reference level. We find out that clicks will decrease by around 20 when moving from desktop to mobile, decrease by around 58 when moving from desktop to tablet. The result implies audiences using desktop are more likely to click on OCF's advertisements, so for the purpose of acquisition, they can consider to increase the desktop budget.

There is no considerable difference among Chinese, English, and mix language keywords. So when buying a new keyword, they do not need to worry about the issue of language selection.

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4.3.3 Activation

4.3.3.1 Descriptive Statistics

In activation, we wish to evaluate users' experience when landing the website. How long do they stay and read the content? How frequent does a user leave as soon as arrival? How many and what kind of interactions do they made?

In OCF's case, the website contains many information placed in different sections (see Figure 2). The ideal behavior of a user is that he or she can stay to explore more information and read more pages. In other words, we consider a high bounce rate as a crucial negative indicator.

Thus, the dependent variable we designate in this stage is "bounce rate". We delete the data with bounce rate at 0%, because a 0% bounce rate could be the consequence of technical problems such as duplicate tracking codes, embedded iframe, or custom event tracking. After the data screening, we have total 494 keywords.

A 100% bounce rate is most common in our data set, meaning that most of the audience land in the page and do not advance to any other page on the website.

Table 15: Bounce rate (January – August, 2017)

Average	Std.	Min.	Q1	Medium	Q3	Max.
0.88	0.17	0.11	0.81	1.00	1.00	1.00

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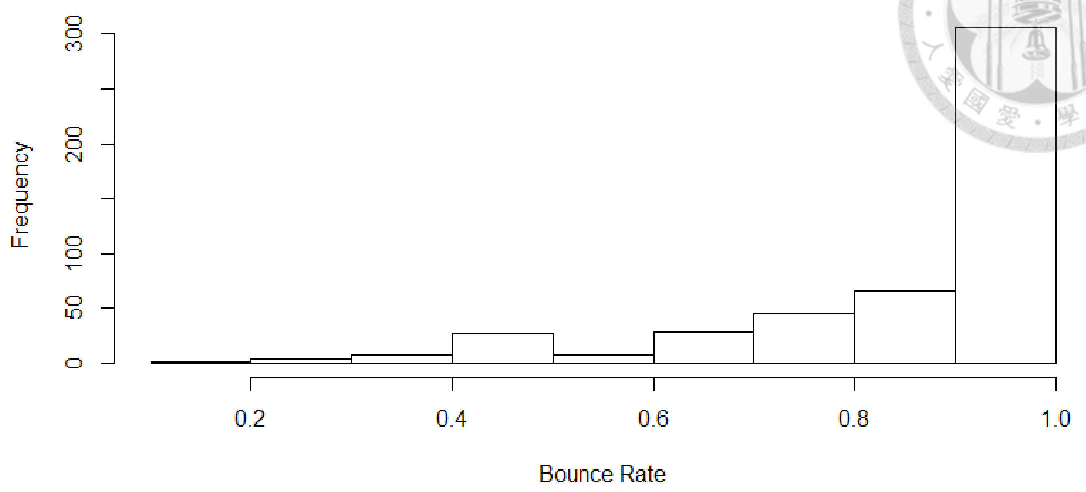

Figure 11: Histogram of bounce rate (January – August, 2017)

4.3.3.2 Regression Analysis

Among the 12 variables, we find six are significant (p-value < 0.05). The regression model is shown below:

$$\begin{aligned} BounceRate_i = {} & \beta_0 + \beta_1 foundation_i + \beta_2 opensource_i + \beta_3 tech_i + \beta_4 gov_i + \\ & \beta_5 event\_cs_i + \beta_6 event\_camp_i + \beta_7 action\_donation_i + \\ & \beta_8 action\_newsletter_i + \beta_9 device\_mobile_i + \beta_{10} device\_tablet_i + \\ & \beta_{11} language\_ch_i + \beta_{12} language\_mix_i + \epsilon_i \end{aligned}$$

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Table 16: Summary of regression analysis (Dependent variable: *BounceRate*)

Independent Variables	Coefficients	P-value	Significant codes
foundation	-0.06266	0.00910	**
opensource	-0.06925	0.00671	**
tech	0.01438	0.51807	
gov	-0.04581	0.26203	
event_cs	0.03252	0.23667	
event_camp	0.06238	0.00382	**
action_donation	0.01957	0.75845	
action_newsletter	-0.02809	0.52092	
device_mobile	0.10160	2.45E-11	***
device_tablet	0.12862	2.58E-09	***
language_ch	0.07081	0.00532	**
language_mix	0.07918	0.20618	
		R^2	0.2663
		Adjusted R^2	0.248

Note. Significant codes: *** p<0.001, ** p<0.01, * p<0.05, · p<0.1

4.3.3.3 Findings and Implications

With respect to keyword's essence, "foundation" and "open source" both has significant impact on bounce rate. The result indicates that traffic comes from keywords

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with the foundation or open source attribute is more likely to have lower bounce rate. It matches our intuition very well – people who search for foundation or open source and then clicked on OCF's website will find the website a great fit to their interests, and they may stay on the site to explore more relevant information.

In the aspect of event, surprisingly, computer science activities do not have strong relation with bounce rate. On the other hand, student camp-related keywords have significant influence on increasing bounce rate. Lots of those keywords are clickbait-like, meaning that the relevance of the keyword and the website is awfully low, making the audience disappointed or confused when landing on, and accordingly leave right away without any other interaction. Therefore, we suggest OCF to forsake the clickbait kinds – such as "children basketball camp", "English summer camp", "YMCA children summer camp" – for they do not really bait many clicks based on the regression results in the acquisition stage (see *section 4.3.2*), and the traffic has strong tendency to have high bounce rate.

Intuitively, we believe that the call-to-action keywords should somehow have a relation with the bounce rate. But there is none, according to our regression model.

As for user device category, the bounce rate is significantly higher on mobile and tables then on desktop computers. At the first glance, there seems to be big problem with the mobile version of website. Nevertheless, if we compare the bounce rate for each device category with the industry benchmark[13] (the "Social Issues & Advocacy" benchmark on Google Analytics) in Table 17, we notice that there are similar trends.

[13] Benchmarking is a function in Google Analytics. There are several industry categories and a user can choose one best matches his or her business. There are 6,052 web properties contributing to the benchmark of "Social Issue & Advocacy" industry.

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Mobile users and tablet users seems to leave the sites quickly on average, which might be caused by the restricted experience users get from mobile browsers, or mobile users may open the site on the go. Although further studies are needed to explain why there is a 10.68% difference between mobile and desktop bounce rate, one thing is clear that there is a big room for improvement for all the device categories in OCF comparing to the benchmark.

Table 17: Bounce rate by device (January – August, 2017)

Device	OCF Keyword traffic	Benchmark
Mobile	90.33%	63.49%
Tablet	86.44%	56.98%
Desktop	79.65%	54.07%

An interesting finding is that audience brought from Chinese keywords also have positive influence on bounce rate than English ones. One possible explanation is that, the majority of the English keywords are about specific programming languages, online collaboration platforms, open source technologies, etc., and there is a higher likelihood that they attract the target audience who are truly interested in the website content and willing to spend more time to read. In comparison, OCF's Chinese keywords contain much more variety and the foci are relatively dispersed.

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4.3.4 Retention

4.3.4.1 Descriptive Statistics

Based on the number of sessions, OCF website holds retention rates steady throughout the years from 2015 to 2017. According to OCF, they are quite satisfied with the current ratio (New visitors vs. Returning visitors = 8:2). Because of the lack of manpower, the website is not updated on a regular basis. Under the circumstances, a frequent returning user is not guaranteed to see new posts every time. Therefore, instead of increasing the frequency of re-visits, they are convinced that attracting new visitors is more important for OCF at the moment.[14]

Table 18: Sessions created by new visitors and returning visitors (January – August)

	2015	2016	2017
New Visitors	18,054	45,785	25,217
Returning Visitors	5,075	12,626	7,051
Ratio (New vs. Returning)	7.81 : 2.19	7.84 : 2.16	7.82 : 2.18

Comparing the behavior between new visitors and returning visitors in keyword advertising traffic, the bounce rate of returning visitors is slightly lower, and their

[14] The comments are from our interview with OCF, which is conducted at OCF's Taipei office on September 25, 2017. The two interviewees are Singing (staff) and ET (website revision volunteer).

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average session duration is almost twice longer than new visitors. The data indicates that the returning users are more likely to have lower bounce rate and the better page depth. Therefore, although the OCF staff mentioned that retention is not the organization's current focus, in order to attract potential high quality audience, we still wish to discover the attributes of keywords that can bring in more returning users.

Table 19: User behavior of new and returning visitors (January – August, 2017)

	Sessions	Bounce Rate	Avg. Session Duration (sec.)
New	11,447	0.89	15.29
Returning	1,951	0.87	30.23
All Visitors	13,398	0.88	17.47

Note. We deleted the data with a 0% bounce rate to calculate the average bounce rate.

We choose "Percentage of New Session" as our dependent variables, which is the estimate of the percentage of first time visits. The lower the percentage implies more sessions created by returning visitors. 0.00 means that all sessions are generated from returning visitors, while 1.00 means this keyword brings only new visitors. Among the 545 keywords[15], the average percentage of new session is 0.82, and almost 40% of the keywords have the percentage at 1.00.

[15] There are total 580 keywords in the original data set; however, when applying the custom report with dimension of "User Type (new visitors and returning visitor)", there are only 545 keyword recorded and presented in the report. The technical issue is still under investigation for further determination.

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Table 20: Percentage of new sessions (January – August, 2017)

Average	**Std.**	**Min.**	**Q1**	**Medium**	**Q3**	**Max.**
0.82	0.25	0.00	0.75	0.89	1.00	1.00

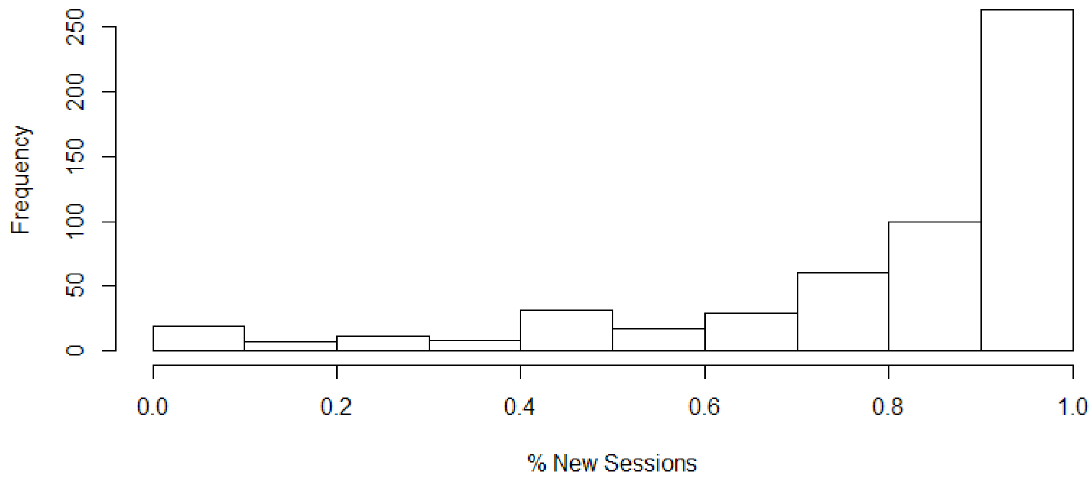

Figure 12: Histogram of percentage of new sessions (January to August, 2017)

4.3.4.2 Regression Analysis

Among the 12 variables, we find three with p-value < 0.05, and two with p-value<0.1. The regression model is shown below:

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$$\%NewSession_i = \beta_0 + \beta_1 foundation_i + \beta_2 opensource_i + \beta_3 tech_i + \beta_4 gov_i + \beta_5 event\_cs_i + \beta_6 event\_camp_i + \beta_7 action\_donation_i + \beta_8 action\_newsletter_i + \beta_9 device\_mobile_i + \beta_{10} device\_tablet_i + \beta_{11} language\_ch_i + \beta_{12} language\_mix_i + \epsilon_i$$

Table 21: Summary of regression analysis (Dependent variable: *%NewSession*)

Independent Variables	**Coefficients**	**P-value**	**Significant codes**
foundation	-0.159590	2.31E-06	***
opensource	-0.207534	9.73E-09	***
tech	-0.063668	0.0529	·
gov	0.053487	0.3431	
event_cs	0.035470	0.3648	
event_camp	-0.054292	0.0774	·
action_donation	0.026801	0.7746	
action_newsletter	-0.133733	0.0272	*
device_mobile	-0.003324	0.8735	
device_tablet	0.005002	0.8651	
language_ch	0.017153	0.6089	
language_mix	-0.026703	0.7535	
		R^2	0.1878
		Adjusted R^2	0.1695

Note. Significant codes: *** p<0.001, ** p<0.01, * p<0.05, · p<0.1

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4.3.4.3 Findings and Implications

The essence of a keyword plays an important role in this stage. Keywords about foundation, open source, and technology all have negative impact on the percentage of new sessions, meaning that these types of keywords are more likely to garner returning users. The result is promising for OCF because their target audience are those who care about open source and technology. To retain those visitors, it seems reasonable to keep investing in keywords of these categories.

Student camp-related keywords also have high possibility to attract returning users, which is surprising. It is difficult to explain based on the current data we have. One possible explanation can be that the students want to check the details of the event multiple times before and during the events.

As for action category, newsletter-related keywords have significant influence on the new sessions percentage. However, for newsletter per se, the organization wishes more new visitors to arrive on the website and subscribe. Thus the high returning rate here is not necessarily a good news. Or, maybe a user cannot decide to subscribe in his or her first visit, so getting a returning user can be turned into a subscriber more easily. Since OCF does not set “newsletter subscription” as a goal in Google Analytics, meaning that the action of subscription is not tracked, it is difficult to make a conclusion based on the current data.

In our previous experiments, user device category always has significant relation to the dependent variables. Nevertheless, the relation is weak when it comes to retention. The impact of language difference is also insignificant.

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4.3.5 Revenue

4.3.5.1 Descriptive Statistics

The main income source of OCF is donation; hence, in the discussion of revenue, we will focus on the data of donation tracked by Google Analytics. The data shows the total number of conversions rather than the actual monetary amount.

The donation project is launched on February 3rd, 2016. There are total 215 conversions: 37% (80) from direct, 27% (58) from social, 26% (55) from referral, 7% (14) from organic search, and 4% (8) from paid search in the year of 2016.

In the year or 2017, there are total 144 conversions: 1 from direct and 143 from referral. However, the number is misleading due to some technical problems[16], which interprets the third party payment website, ECPay, as the users' source, and accordingly all conversions are attributed to referral channel.

We assume that the user channel distribution in Step 4 (in Figure 3) is proportional to that of Step 3. Therefore, we redistribute the number in Step 4 base on the percentage in Step 3. The conversions in the year of 2017 attributed from each channels after adjustment are shown in the table below.

[16] We have asked about the problems through interview and emails with OCF staffs and a director, yet the detailed adjustment in 2017 is still under investigation for further determination.

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Table 22: Redistribution of the number in Step 4 (January – August, 2017)

Channel	Step 4: complete donation (A)	Step 3: confirmation (B)	Adjusted conversions ($C_i = B_i \times \sum A_i / \sum B_i$)
Direct	1	81	65
Social	0	53	42
Referral	143	22	18
Organic Search	0	23	18
Paid Search	0	1	1
Total	144	180	144

Table 23: Conversions by channel (January – August, 2017)

Channel	2016	2017*	Change
Direct	80	65	-19%
Social	58	42	-27%
Referral	55	18	-68%
Organic Search	14	18	31%
Paid Search	8	1	-90%
Total	215	144	-33%

Note. The numbers in 2017 are adjusted (see Table 22).

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After the redistribution, we still have only 1 conversion from keyword advertising traffic in 2017, and we are unable to identify which keyword it is, which makes us incapable for running the regression.

In 2016, there are 8 conversions come from 5 different keywords tracked in Google Analytics. Therefore, we will use data in 2016 to conduct our regression analysis in this section.

4.3.5.2 Regression Analysis

Different from the previous linear regression models, in this stage we designate "conversion" status of keywords as the binary dependent variable (0- no conversion, 1- conversion has been made). The logistic regression model is shown below:

$$
\begin{aligned}
Conversion_i = \beta_0 + \beta_1 foundation_i + \beta_2 opensource_i + \beta_3 tech_i + \beta_4 gov_i + \\
\beta_5 event\_cs_i + \beta_6 event\_camp_i + \beta_7 action\_donation_i + \\
\beta_8 action\_newsletter_i + \beta_9 device\_mobile_i + \\
\beta_{10} device\_tablet_i + \beta_{11} language\_ch_i + \beta_{12} language\_mix_i + \epsilon_i
\end{aligned}
$$

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Table 24: Summary of regression analysis (Dependent variable: *Conversion*)

Independent Variables	Coefficients	P-value	Significant codes
foundation	20.6938	0.99596	
opensource	4.0493	0.00897	**
tech	16.9061	0.99670	
gov	-2.5105	0.99986	
event_cs	-18.2863	0.99855	
event_camp	-11.5851	0.99809	
action_donation	-18.9709	0.99948	
action_newsletter	-13.1364	0.99930	
device_mobile	-1.4169	0.24802	
device_tablet	-19.6790	0.99769	
language_ch	0.6917	0.55323	
language_mix	-17.2781	0.99937	
		Null Deviance	57.493
		Residual Deviance	35.039

Note. Significant codes: *** p<0.001, ** p<0.01, * p<0.05, · p<0.1

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4.3.5.3 Findings and Implications

Even though we have found one independent variable (*opensource*) has significant impact on conversions (p-value < 0.01), given the counts of conversion are too small, this results may not be very meaningful. In this case, keyword marketing is useful for building brand awareness and exposure, but it might not be the best way to create conversions.

4.4 Summary

According to the results, some attributes such as “foundation” and “open source” have strong impacts throughout most of the stages. These kinds of keywords are worth buying and keeping exploring. Some attributes are only influential in particular stages. For instance, the computer science related event has tendency to accrue clicks, while student camp event has impact on bounce rate. Therefore, the organization can invest in different kinds of keywords by following their current strategy or for the purpose to fulfill the urgent needs. User device category is crucial in the first two phases (acquisition and activation), yet it seems not very important when it comes to retention and revenue. As for the language difference, it should not be the top priority to consider when buying a keyword.

The significances and the impacts (“+” as positive, “–” as negative) of the independent variables for each stage in the AARRR model are presented in Table 25.

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Table 25: Summary of regression analysis in AARRR model

Stage	Acquisition	Activation	Retention	Revenue
Variables	Click	BounceRate	%NewSessions	Conversion
foundation	+ ***	− **	− ***	
opensource		− **	− ***	+ **
tech			− ·	
gov				
event_cs	+ **			
event_camp		+ **	− ·	
action_donation				
action_newsletter	+ *		− *	
device_mobile	− *	+ ***		
device_tablet	− ***	+ ***		
language_ch		+ **		
language_mix				

Note. Significant codes: *** p<0.001, ** p<0.01, * p<0.05, · p<0.1.

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We summarize the implications in the tables below. Only the significant attributes (p-value < 0.1) are listed, with the mark "+" as effective and worth investing and the mark "–" as the indicator of poor performance and need to be adjusted.

Table 26: Summary of implications and suggestions

<table>
<tr><th></th><th>Acquisition</th><th>Activation</th><th>Retention</th><th>Revenue</th></tr>
<tr><td rowspan="4">Keyword Essence</td><td>foundation (+)</td><td>foundation (+)</td><td>foundation (+)</td><td></td></tr>
<tr><td></td><td>opensource (+)</td><td>opensource (+)</td><td>open source (+)</td></tr>
<tr><td></td><td></td><td>technology (+)</td><td></td></tr>
<tr><td colspan="4">Based on the promising outcome, the current keyword categories are worth keep investing, except for the government-related ones, whose relationships with the measurements are as not satisfying.</td></tr>
<tr><td rowspan="3">Event Type</td><td>event_cs (+)</td><td></td><td></td><td></td></tr>
<tr><td></td><td>event_camp (–)</td><td>event_camp (+)</td><td></td></tr>
<tr><td colspan="4">Reinforce the computer science-related event promotion in AdWords.
Forsake the clickbait-like ones in student camp category, for they perform poorly both in acquisition and activation. (Although they work well in retention, the reason needs further investigation for determination.)</td></tr>
<tr><td rowspan="2">Action Type</td><td>newsletter (+)</td><td></td><td>newsletter (+)</td><td></td></tr>
<tr><td colspan="4">Pursuit awareness and exposure by newsletter keywords. Set a new goal of "newsletter subscription" in Google Analytics are also suggested, so the relationships between retention and subscription can be examined.
donation has no strong impact throughout the stages. Keyword advertising may not be the best way for conversion.</td></tr>
</table>

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Table 27: Summary of implications and suggestions (continued)

<table>
<tr><th></th><th>Acquisition</th><th>Activation</th><th>Retention</th><th>Revenue</th></tr>
<tr><td rowspan="2">Device</td><td>mobile (−)
tablet (−)</td><td>mobile (−)
tablet (−)</td><td></td><td></td></tr>
<tr><td colspan="4">Mobile and tablet users seem to click less and leave the sites quickly on average than desktop users. In addition, there is room for improvement for all the device categories in OCF comparing to the benchmark.</td></tr>
<tr><td rowspan="2">Language</td><td></td><td>Chinese (−)</td><td></td><td></td></tr>
<tr><td colspan="4">Language is the last priority to consider when buying keywords.
English keywords have lower bounce rate than Chinese ones, might because most English keywords are about specific technologies, and better cater the target audience.</td></tr>
</table>

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Chapter 5

Conclusions

5.1 Research Purpose and Contribution

Many small NPOs share the common struggle of the shortage of funds when it comes to marketing. Thus, they need to strive to seize every resource and opportunity. Google Ad Grants program is one of the opportunities that widely used by NPOs globally, which provides free in-kind keyword advertising service. Nevertheless, even given the considerable budgets, how to select the right keyword wisely remains a great challenge faced by advertisers.

In this thesis, our research purpose is to reveal the possibilities for small NPOs to better utilize the limited resource and optimize their online marketing performance. In order to make use of the opportunity given from the Google Ad Grants program, we accordingly focus on the keyword advertising. Our goal is to help NPOs identify the best-suited and most effective keywords. Specifically, we wish to find out the particular attributes of the keywords that can affect advertising performance in different phases of customer lifecycle and conversion behavior designated by the AARRR model.

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The contribution of our thesis is the pioneering research in the field of Taiwan-based NPO focusing on the interplay between keyword attributes and advertising performance. The study provides guidelines for future researches and practitioners regarding the impact of keyword attributes in different phases in customer lifecycle and conversion behavior. From an academic perspective, our attempts to uncover the improvement opportunities for Taiwanese NPO and to explain the relationships between keyword attributes and advertising effectiveness is innovative as well as pioneering. The reasoning behind attribute category and variable designation, the statistical model selection, and the approaches to analyze and interpret are all adoptable for future studies. From an advertiser's point of view, our findings can help them to re-examine their existing keywords, and enable them to select and invest in keywords based on a mathematically-proved methodology, rather than mere intuitions.

5.2 Findings and Suggestions

In our empirical analysis, we designate 12 keyword attributes in five categories: 1) Keyword Essence: *foundation, open source, technology, government*; 2) Event Type: *computer science event, student camp event*; 3) Action Type: *call for donation, call for newsletter subscription*; 4) Device Category: *mobile, tablet* (desktop as reference level); 5) Language: *Chinese, mixed language* (English as reference level). The relationships between the attributes and the phases of customer lifecycle and conversion behavior – acquisition, activation, retention, referral – are being observed and explained.

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In the category of keyword essence, the overall outcome is promising throughout all the stages, indicating that the current keyword attributes are worth investing as well as keeping exploring, only except for the *government*-related ones, however, whose relationships with the measurements are as not satisfying.

In terms of event type, the promotion of the *computer science*-related event in keyword advertising should be reinforced, based on the positive results in visitor attracting. On the other hand, we recommend the organization to forsake or adjust the clickbait-like ones in the *student camp* category, for they perform poorly both in acquisition and activation stage.

As for call for action keywords, *newsletter* has strong tendency to garner clicks, making them good choices to build awareness. They also work well in retention; we suggest setting a goal of “newsletter subscription” in Google Analytics in order to track and understand the relationships between retention and subscription. Keyword advertising may not be the best way to drive conversions, for *donation* attribute has no significant impact throughout the stages.

Device-wise, mobile and tablet users seem to click less and leave the sites quickly on average than desktop users. Yet there is no obvious difference in device when it comes to retention and revenue phase. Additionally, in the perspective of user experience, there is room for improvement for all the device categories in OCF comparing to the benchmark.

Language seems to be the last priority to consider when buying keywords, which hardly has significant influences. The only exception is the activation stage, where English outperforms others; one possible explanation is that most English keywords are about specific technologies, and thus better cater the target audience.

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To summarize, the research results indicate that some attributes have strong impacts throughout most of the stages, which makes them good options for investment. Meanwhile, some attributes are only influential in particular phases. Therefore, the organization should prioritize their keyword selection by following their current strategy or to fulfill the urgent needs.

5.3 Limitation and Future Work

Some different adaptations, tests, comparisons, and analysis have been left for the future due to the time limit and resource constraints. First, our regression models focus on the relationship between each independent variable (keyword attribute) and the dependent variable (performance measurement), which is the main effect. Among the keyword attributes, we are aware that the independent variables might interact with each other in a more complex reality. Therefore, the interaction effects can be taken into account when conducting the further analyses.

Secondly, user behavior, such as bounce rate or re-visit, can be affected by the website content, interface design, loading time, or other experience. In our discussion, we solely focus on the keywords that the users click on, and we believe that reflects user’s intention at the moment, but we are also aware of the limitation; hence, we can further conclude the analysis of website content, such as user research, eye tracking heatmaps, etc.

In terms of research resource, with access to more data, we can try to discover measurements that interpret the relation between keyword advertising and the referral

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behavior or the referral outcome. In addition, in our case study, there is only one goal, “donation process completion”, set in Google Analytics. With more goals designed, such as “newsletter subscription” or “media kit download”, we can have a broader view on the overall marketing performance.

Lastly, we have identified the potential influential keyword attributes in the empirical analysis. Based on our suggestions, we can conduct follow-up experiments by changing keyword strategy and carrying out continuous A/B tests, and thus verify the research findings.

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