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Conversion potential: a metric for evaluating search engine advertising performance

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Abstract

Purpose – This research is based on the premise that current metrics for Search Engine Advertising (SEA) are misleading and do not sufficiently allow managers to evaluate traffic and conversions simultaneously. We conceptually develop and assess Conversion Potential (CvP) as a unifying construct for both measuring and evaluating the performance of SEA campaigns.

Methodology – To validate the construct of CvP, we utilize a dataset of nearly seven million records covering almost three years of a multi-million dollar keyword marketing campaign from a major US retailer.

Findings – Results empirically validate how CvP measures both campaign traffic and sales in SEA, using the optimization factor of ad rank, which is one of many possible factors.

Research limitations – Although the dataset is large and covers a lengthy period of time, it is limited to one company in the retail sector.

Implications – The research instantiates CvP as a metric for overall SEA account performance, while demonstrating that it is a practical tool for future campaign planning. The metric simultaneously incorporates a sales ratio and a traffic ratio.

Originality/value – To the best of our knowledge, this is the first study to formalize and provide a working definition of CvP in the academic literature. The contribution is a theoretical and practical managerial framework to mutually evaluate, measure, and make decisions about SEA efforts.

Keywords: Search marketing, Online metrics, Paid search, Pay-Per-Click (PPC), Internet advertising

Introduction

Search Engine Advertising (SEA) serves as a central revenue stream for major search engines (Jafarzadeh *et al.,* 2015), such as Baidu, Google, Yandex, and Bing. Known as keyword advertising, search engine marketing, and pay-per-click, SEA shaped the nature of the web (Laffey, 2007) and is a critical marketing component for many organizations (Quinton and Khan 2009).

SEA generates billions in revenue each year for the major search engines. Parent company Alphabet Inc. (NASDAQ: GOOG, GOOGL) reported Google's 2015 ad revenue of 74 billion US dollars, with SEA accounting for the majority of total revenue (Alphabet, 2016). In 2015, SEA was the largest category of spending by advertisers in the US and is expected to continue commanding a large share of total future digital ad spend (eMarketer, 2016). As a key form of communication for both consumers and businesses (Stone and Woodcock, 2014), a major driver of growth (Bucklin and Sismeiro, 2009), and a major business model for the search engines, SEA is an area of research importance to practitioners (Weis, 2010).

Online consumers often begin their searches at the macro level through the use of search engines (Hofacker and Murphy, 2009). The basic concept of SEA is that advertisers bid on keywords in order to have the search engine display their ads on search engine results pages (SERP) in response to matching queries submitted by searchers (c.f., Jansen *et al.,* 2009). Keyword *bids* represent the amount an advertiser is willing to pay when a searcher clicks on their ad. Bids serve as a major factor impacting whether a search engine displays that ad (also known as an *impression*) and where an ad is shown relative to other ads (also known as *ad rank*). Bids influence campaign cost control; impressions and ad rank depict the likelihood that an ad was seen by potential customers. *Sales* is typically used to evaluate the overall success of a campaign.

While keyword bids, impressions, ad rank, and sales figures are clearly important within the overall SEA strategy, they represent singular measures of a campaign's efficiency and effectiveness. As we will demonstrate, there are flaws inherent in the interpretation of data with commonly used SEA measures. Decision makers may make costly mistakes because of misleading insights about account performance. For instance, Park and Fesenmaier (2012) found that using unweighted data to estimate advertising effectiveness may lead to considerable over estimation of success. Because SEA campaigns use a multitude of independent variables, there is a need for robust metrics that account for the combined influence of factors operating within SEA campaigns. Such metrics may help mangers to make better informed decisions across multiple levels of advertising such, as accounts, campaigns, ad groups, and ads.

Although the search engine marketing field is trending in the academic literature (Pomirleanu *et al.,* 2013), limited research exists on the theoretical conceptualization of SEA performance (Jafarzadeh *et al.,* 2015), and performance measurement problems seem to be commonplace in marketing. In their analysis of nearly 1,000 studies, Katsikeas *et al.,* (2016) uncovered problems with both the operationalization and conceptualization of marketing performance outcomes. Within a growing stream regarding singular performance metrics (King *et al.,* 2015), there is limited research investigating the use of combined metrics. This study advances our understanding of SEA by introducing *Conversion Potential (CvP)* as a managerially useful and combined metric for planning and evaluating campaign performance using multiple SEA factors.

The paper's objective is to present working definitions, results, and ideas for future research aimed at extending and understanding this metric.

Search Engine Advertising (SEA) Background

Prior Research on SEA

As noted by Rangaswamy *et al.,* (2009), SEA provides unique opportunities impacting businesses in a variety of ways and with far-reaching consequences. A growing body of academic research reports on various aspects of SEA, such as: keyword performance for newly established campaigns (Abou Nabout, 2015), intrinsic and extrinsic keyword characteristics (Klapdor *et al.,* 2014), optimal ad pricing (Sen *et al.,* 2008), personalization of client-side keyword profiles (Bilenko and Richardson, 2011), effects of search result design (Edelman and Lai, 2016), the impact of multiple search ad exposure on consumer intent to purchase (Fulgoni and Mörn, 2008); relationships between keywords (Rutz *et al.,* 2012); generic versus branded search (Rutz and Bucklin, 2011), search engine marketing efficacy (Blake *et al.,* 2015), and click behaviors (Jerath *et al.,* 2014).

Jafarzadeh *et al's.* (2015) review of 101 papers from 72 journals classified the SEA literature into four streams of research (e.g., law-related, overview/review, mechanisms, and behavioral/practical) and ten topical areas such as bidding strategy, keyword selection, click fraud, and searcher behavior, to name a few. Their analysis concluded that current literature lacks integration and synthesis across the streams and topics of SEA. Given the recent emergence of SEA as a new form of online marketing, their conclusion is quite fitting to the situation. Much work remains in order to understand this complex form of advertising.

Overview of the SEA Process

There are several terms and metrics commonly used in the SEA industry (Fain and Pedersen, 2006; King *et al.,* 2015; Vattikonda *et al.,* 2015), and one must have a base functioning knowledge of these in order to follow the ideas proposed in this study. Select elements are discussed below and illustrated in Figure I.

--- Insert Figure I. ---

In SEA, advertisers create ads and bid on keywords that relate to some product they are providing. Using various algorithms, search engines match these phrases to queries submitted by searchers. When a searcher's query is effectively matched with an advertiser's phrase and the advertiser's bid is high enough, an ad may be displayed to the searcher on a SERP, along with ads of other advertisers who are also bidding on the same or a similar keyword. The display of such ads is an *impression*. Impressions help searchers become aware of information based on the questions or problems they would like to solve. In SEA, impressions would not take place without someone first making a query by inputting in keywords. Thus, impressions contribute to the generation of consumer awareness, and they serve as an indicator to advertisers of potential traffic they might experience on their website.

After an impression is observed, if a searcher clicks an ad and arrives on the advertiser's landing page, this results in a *click*. The click metric shows actual traffic to a landing page and gives an advertiser a sense of how many people were interested in learning more about their ad and/or product. The *click-through-rate (CTR)* is a common traffic metric (Vattikonda *et al.,* 2015) depicting the ratio between clicks and impressions. CTR is calculated as clicks ÷ impressions, representing the number of ad clicks relative to the number of times that ad was shown in a given period. CTR is one indicator of ad effectiveness, as it shows the impact of an ad in creating actionable interest with a unique searcher. Importantly, clicks and CTR indicate to advertisers that consumers were interested in researching their offering.

After clicking an ad and arriving on the landing page, if the searcher engages in a desired goal or behavior, this action is known as a *conversion*. Numerous types of conversions exist such as completing a form, signing up for a newsletter, downloading content, or making a purchase (a.k.a., a *sale* or an *order*). In the case of purchases as conversions, the *sales revenue* generated from the conversion might be used to define the value of that customer. In SEA, *conversion rate (CR)* is the ratio of users completing a desired behavior in relation to the number of ad clicks. CR is also widely used in practice and reflects an ad's contribution to successful completion of goals. For example, if an ad resulted in 1,000,000 clicks, and 20,000 of those site visitors made a purchase, the CR would be 2% (20,000 ÷ 1,000,000).

The Role of Ad Rank in SEA

SEA relies on the concept of optimization which includes all of the strategies and tactics that one might use to improve performance. There are numerous studies contributing to our understanding of optimization such as bidding strategies, ad quality, keyword characteristics, keyword frequency, brand mentions, calls-to-action, and ad extensions (c.f., Jafarzadeh *et al.,* 2015; Klapdor *et al.,* 2014). We assume that optimization factors can be ordered or grouped in some manner, giving them a ranking. One such factor is *Ad Rank*.

Ad rank signals to the advertiser whether and where an ad is shown on a SERP in relation to other competing ads. Ads can be displayed directionally in one of three locations on desktop devices: above the organic results listing (i.e., north position), to the right of the organic results listing (i.e., east position), or below the organic results listing (i.e., south position). Because of screen size limitations (Grewal *et al.,* 2016), mobile devices show ads in the north and south only. Search engines recalculate ad rank for each ad in the auction with every search query and differ in methods used to determine where an ad will be positioned. For instance, Bing uses two factors in their proprietary ad rank formula: ad quality and keyword bid. Conversely, Google's ad rank formula scores ads based on keyword bid, ad quality, landing page quality, and the expected performance based on the use of extra relevant information in the ad known as "ad extensions." While conducting this research, Google announced the elimination of right-side ads on desktop devices (McGee, 2016), but other search engines such as Bing still use this east position. The long term impact of Google's removal of right-side desktop ads is unclear at this juncture (Ballard and Taylor, 2016). Regardless of an ad's directional position on a SERP, there remains an ordered ranking when comparing ads. For instance, an average ad ranking between 1 and 5 means the ad is most often appearing above competitive ads with average ad rankings between 6 and 10. It is noteworthy that few searchers go beyond the first two SERPs (Richardson *et al.,* 2007), and ad positions on the first SERP attract about 70% of the overall traffic (Brooks, 2004a). Advertisers therefore compete for ad rank (Chan and Park, 2015) using different strategies to get their ads to show in desired positions within a SERP (Yuan *et al.,* 2015). One such strategy is the advertiser's bid, which might be calculated based on CTR and CR (Abou Nabout, 2015).

Research findings show mixed results regarding ad rank and performance. Liu *et al.,* (2009) found that ads appearing in top ad positions resulted in higher clicks than ads at the bottom of the same page. A study by Agarwal *et al.,* (2011) evaluated the impact of ad placement on revenues and profits, reporting that while CTR decreases with an ad's position, conversion rates increase, especially when more specific keywords are used. Interestingly, middle positions can produce powerful results. Ghose and Yang (2009) detected the effect of an ad's position on a user's click and conversion behaviors, finding that profits are often higher at the middle of a SERP, rather than the top or bottom. Ayanso and Karimi (2015) found that ad position for web-only advertisers is dependent on a bid value and the relevancy of an ad, but it is bid-dependent only for multi-channel retailers. Clearly, more research is needed to better understand ad rank and performance issues within the context of SEA strategy. While the purpose of this study is not to predict ad rank, we use this optimization factor as a means for developing and testing CvP.

A SEA Metric Problem

Unfortunately there is currently limited to no academic literature regarding SEA metrics. Yet, marketing practitioners need workable metrics that can be linked with their organization's highest priority goals (Järvinen and Karjaluoto, 2015). By metric, we mean the commonly accepted business definition of a standard of measurement for accessing, in this case, a process. Metrics are used to quantify and compare phenomena across observations, such as time, to facilitate understanding (Farris *et al.,* 2015). Although advertisers struggle in evaluating online metrics (Edelman 2014), the right metrics can enable marketers to take better risks and make informed decisions (Pauwels 2015).

Within SEA, CTR and CR are commonly used metrics and important to advertisers because they represent a measure of desired behavioral responses achieved as a result of an advertising effort. To illustrate this point, in Table I, take the hypothetical of five keywords that each generated 100 impressions within the same campaign and ran for the same amount of time. For simplicity purposes, assume optimization efforts and advertiser inputs (e.g., bids, landing page, ad, ad quality, product offer, etc.) and all other performance metrics (e.g., average CPC, cost-per-conversion, etc.) are held constant. In this example, we evaluate five keywords; however, we could use the same approach in evaluating other SEA elements such as campaigns, ads, ad groups, or even entire accounts. Based on this data, keyword A and/or E might be perceived as best because of the 100% CTR for keyword A and/or the 100% CR for keyword E. However, we reasonably conclude that neither keyword A or E is performing extraordinarily well. The 100% CTR of keyword A does not shed light on the fact that site visitors were not converting into sales upon arriving at the site. Although keyword E yielded a perfect CR of 100%, the metric masks the amount of traffic being driven to the site. Putting these extremes aside and drawing attention to the CTR and CR for keywords B, C, and D in the middle, the situation becomes even murkier.

--- Insert Table I. ---

Is keyword B, C, or D the superior best performer when looking at CTR and CR in Table I? One might think keyword B because of the second highest CTR of 80% or perhaps keyword D because of the second highest CR of 25%. Yet, these high percentages are quite misleading. In actuality, Keyword C is the best performer compared to the other four keywords, even though it falls in the middle on both metrics. To explain, Table II below presents the impression, click, and conversion data used to generate the CTR and CR from Table I. The CTR and CR for keyword C appears to be performing moderately, and in the middle, yet, the CTR and CR metrics masked the fact that keyword C actually resulted in more sales (5) compared to other the four keywords combined.

--- Insert Table II. ---

We conclude that CTR and CR are metrics with deficiencies and can result in incorrect conclusions by campaign decision makers. CTR does a good job of measuring consumer interest via the traffic ratio, but it does nothing for measuring consumer behavior via the sales ratio. Similarly, CR can measure behavior via the sales ratio but does nothing in terms of measuring interest via traffic volume. Therefore, there is a gap in evaluating performance as neither CTR nor CR provides comprehensive insights into a campaign. As shown by the blank cells in Table III, there lacks a metric between two important evaluation lines of traffic and sales.

--- Insert Table III. ---

To provide a more comprehensive perspective, we propose a metric that simultaneously captures both the traffic aspect of performance as well as the performance aspect of the traffic that results in a conversion, which improves informed decision-making for keyword advertising campaigns relative to traffic or conversion metrics alone. We introduce *Conversion Potential (CvP)* to the academic literature by building upon an initial conceptualization in the practitioner literature offered by Brooks (2004a, 2004b). In his study, CvP was only defined operationally. While highly insightful, as well as inspirational regarding the impetus of our research, Brooks' work was published as two short executive summaries for industry-led thought papers, leaving many open questions concerning theoretical conceptualization, methodology, and empirical support. Table IV illustrates that CTR by itself measures the traffic aspects of keyword advertising, but does not measure the sales aspect. Similarly, CR measures the sales aspect, but not the traffic. CvP, however, encompasses both the traffic and sales ratios. In the sections that follow, we build the case that CvP may be a highly useful metric for evaluating how effective are the keywords in getting searchers to look at advertisements and also the efficiency of ads in generating clicks and sales.

--- Insert Table IV. ---

Responding to Jafarzadeh *et al's.* (2015) call to address gaps in the SEA literature and MacInnis' (2011) challenge to offer new conceptual marketing contributions, this research extends Brooks' (2004a, 2004b) initial work in several ways. First, we formally define the concepts inherent in CvP, generalizing the concept beyond Brooks' specific study, which included only an implied operationalization. Second, the research offers a more accurate operational definition as our approach accounts for the growing importance of relative measures of performance (Keiningham *et al.,* 2015). Third, we submit the entire CvP construct to empirical evaluation and statistical testing to validate its managerial worth. The outcome of this research could have profound impacts for an enriched understanding of SEA metrics and performance measurement.

Conversion Potential

To build a constructional framework for Conversion Potential (CvP), we must begin by developing a conceptual and an operational definition for a highly related concept, *Click Potential.*

Click Potential (CP) is conceptually defined as the overall opportunity of an ad to be viewed and therefore clicked. We posit that CP is a predictor factor, or a summation of predictor factors that influence the possibility of an ad attracting a searcher's attention and generating possible clicks. CP has an underlying attribute of *relative impressions*, which is the change in the number of impressions with the change in another attribute, given some baseline number of impressions. Therefore, CP may be operationalized as:

$$CP = RI \times CTR, \text{ where } RI = I / BI \times 100\%$$

where:

CP = Click Potential
RI = Relative Impressions
CTR = Click Through Rate (CTR)
I = Impressions
BI = Baseline Impressions

The reason we need relative metrics is because absolute metrics do not provide sufficient detail. CTR and CR are *absolute metrics* because they represent an aggregate metric, regardless of observed changes in any other attribute. While absolute metrics are often used to assess organizational performance (Vattikonda *et al.,* 2015), relative metrics are becoming increasingly important tools in marketing (Keiningham *et al.,* 2015). *Relative metrics (a.k.a. incremental metrics)* represent an absolute metric in relation to some other factor, such as a baseline measure, time, competition, size, past performance, industry benchmark, etc. When viewing metrics from a relative perspective, managers can evaluate potential changes in one variable against another.

Using the notion of CP described above, we define Relative Click Potential (RCP) as the extent to which modifications of an optimization factor impact a traffic goal, such as clicks to a website. The value of RCP is that it can inform advertisers of the effect of strategy changes on overall traffic goals. RCP may be operationalized as the percentage change in CP, compared to a baseline that results from a change in an optimization factor, as expressed in the following equation:

$$RCP = -(1 - CP/BCP) \times 100\%$$

where:

RCP = Relative Click Potential
CP = Click Potential

BCP = Baseline Click Potential

Although a variety of optimization factors might be examined to assess RCP, this research builds on Brooks (2004a, 2004b) prior work by using ad rank as an optimization factor to analyze its effect. A goal of this research is to validate a unified CvP framework for evaluating SEA efforts. We operationalize RCP in this study as the summation of all clicks at a given factor's rank divided by the sum of impressions at rank number one for that factor. Rank #1 serves as the baseline. In practice, the baseline would generally have the greatest number of clicks, but this is not a necessary assumption.

Brooks (2004a, 2004b) is credited with examining how changing factors might impact site traffic (i.e., clicks) and sales (i.e., conversions), coining the phrase "conversion potential" as a measure of the change in number of conversions based on the change in some other attribute. We therefore formally introduce a conceptual definition of Conversion Potential (CvP) as the opportunity for future conversions to occur based on past traffic and sales. Based on the CP and the CR, CvP therefore evaluates CTR and CR simultaneously in a measure of effectiveness and efficiency of a campaign. Of interest to SEA decision makers charged with evaluating SEA efforts, CvP takes into account both site traffic and conversions. We concur with Brooks' (2004a, 2004b) operationalization of CvP as:

$$\text{CvP} = \text{CP} \times \text{CR} \times 100\%$$

where:
CvP = Conversion Potential
CP = Click Potential
CR = Conversion Rate

Working from the discussion of relative metrics, Relative Conversion Potential (RCvP) can be defined as the volume of potential conversions based on the CP and the CR compared to a baseline value. RCvP gauges the percentage change in CvP that may result because of the change in an underlying optimization factor. The managerial value of the RCvP metric is that it gives decision makers a measure to simultaneously evaluate the overall effectiveness of a campaign because it combines at least <u>four</u> other variables, of both traffic and sales, into a single relative measure. We propose an operationalization of RCvP as:

$$\text{RCvP} = (1 - \text{CvP}/\text{BCvP}) \times 100\%, \text{ where BCvP} = 1 \times 100\%$$

where:
RCvP = Relative Conversion Potential
CvP = Conversion Potential
BCvP = Baseline Conversion Potential

The possible managerial implications of leveraging RCvP as an evaluation metric are many, by informing business decisions. With a limited budget, RCvP can be used to make evaluations across ads, ad groups, campaigns, accounts, etc. and provide insights concerning SEA efforts. Conversely, if there was excess budget, RCvP helps guide decisions about reallocating excess resources. If an advertiser wanted to consolidate, RCvP determines where and how consolidation might occur within an account. RCvP also communicates to executives, clients, and others, how campaigns are performing without overwhelming them with data.

A hypothetical example in Table V shows three advertising campaigns. Campaign F, with 100 impressions and 100 clicks, has a CTR of 100% and serves as the baseline campaign for determining RCP. To calculate RCP, we used the summation of all clicks divided by the sum of clicks for some optimization factor. For conversions, we calculate the RCvP across the campaigns, based on changes from the baseline in Campaign F. CvP informs us that, considering both traffic and sales, campaign G is 3.9% of the CvP of campaign F, and campaign H is .10% of campaign F. Therefore, in this example, implementing campaign H would cause a 99% reduction in CvP, based on volume (i.e., traffic differential between campaigns F and G) and sales (i.e., conversion differential between campaigns F and G).

--- Insert Table V. ---

Although the CvP could be calculated using any ordered optimization factor, we used ad rank in this research based on several reasons. First, ad rank is a measure inherently tracked in most SEA campaigns and is well researched, so it is a demonstrative way to show the applicably of the analysis (Chan and Park, 2015; Jansen, Liu, and Simon, 2013). Second, the overall goal of this research is to demonstrate the value of the theoretical concept of CvP, which we believe that ad rank would do. Third, the use of ad rank clearly demonstrates a practical implementation of the concept of CvP, although in practice any variable could be utilized, such as keywords (Jerath, Ma, and Park, 2014) or device type (Grewal et al, 2016). Again, our primary research goal is to demonstrate the applicability of CP and CvP and the focus is not on one empirical attribute.

Research Hypotheses

We present two hypotheses to test the validity of the CvP constructional framework.

H1: *There will be a significant difference in Click Potential (CP) based on ad rank.*

Building on our conceptualization, one would expect a significant difference in CP by ad rank. Given that the goal of most SEA campaigns is to get potential consumers to click on a given advertisement, the click is a commonly used measure of potential interest in an ad and a campaign typically aims for relatively high click volumes. With a large number of clicks, an ad can direct more traffic to an organization's website. Therefore, click-through-rate (CTR) is an important performance measure of a campaign, as it provides a sense of the number of consumers who are interested in their ads. By investigating CP at each rank, we can calculate the Relative Click Potential (RCP) and statistically test if a significant change exists in CP among different ad ranks.

H2: *There will be a significant difference in Conversion Potential (CvP) based on ad rank.*

Based on prior SEA research and our notion of CP, one would expect a significant difference in CvP by ad rank. Although the number of clicks can be adopted as a simple measure of performance, it alone cannot guarantee post click-through behaviors. In other words, click volume alone cannot indicate who will end up making a purchase or becoming a sales lead after clicking on an ad. The Conversion Rate (CR) provides advertisers a more accurate measure of the effectiveness of the ad campaigns. As such, a higher CR for ads with certain ranks would indicate the ad rank's impact. However, conversation rates do not tell the full story, as the CR can be high at a given ad rank, but the volume of traffic can be insignificant. Therefore, we need to examine CvP, which examines both the CR and the traffic volume. By investigating CvP at each ad rank, we can calculate the Relative Conversion Potential (RCvP) at each rank and then statistically test if there is a significant change in CvP among ad ranks.

Methodology

Dataset

To evaluate the aforementioned concepts, we use a large scale dataset from a major U.S. retailer, with both brick-and-mortar and online sales presences, to examine performance differences using distinct keyword-ad combinations and daily metrics. The major nationwide retailer specializes in a variety of novel and high end retail products, both online and stores, primarily in shopping malls. The data is derived from keyword advertisements during a 33-month period. The dataset is quite rich in that it includes keywords that triggered ads, ad copy, ad rank, and consumer responses such as clicks and sales data associated with every keyword. As noted from multi-million dollar spend of the advertising campaign, along with the multi-million dollar revenue, the retailer has a major presence in the retail sector.

The dataset contains approximately seven million records from nearly 40,000 keywords and 55,000 advertisements. The set includes a record for every day in which one of the keywords triggered an ad. Each record has a variety of information by keywords for a given day including: keywords triggering the ad, number of impressions, number of clicks, average cost-per-click, number of conversions, sales revenue, and number of orders. We assume that there is no significant difference in ad quality for keyword-ad pairs, as this was a well-developed SEA effort from multiple years. The data is considered to be a rich source of information in which to investigate the theoretical constructs and hypotheses. There has been limited keyword advertising research that validates theoretical concepts with actual data, which is the goal of our research.

Results

Because few searchers go beyond the first two SERPs (Richardson *et al.,* 2007), subsequent analysis focuses only on the top sixteen ad ranks listed. We did this considering the low rate of clicks for individual ads on the subsequent SERPs relative to the high rate of clicks on the first two pages. For each of the 16 ad rank groups, descriptive statistics were calculated and are presented in this section in their natural form. However, hypothesis testing was carried out using one-way ANOVA and post-hoc Tamhane's T2 test on the log transformation data.

Aggregated statistics from the top sixteen ad ranks are shown in Table VI. Consistent with prior studies of user's click behaviors (Lee et al., 2013), ads on the first two SERPs led to about 99% of the total sales. Therefore, payment for ads listed on the first two SERP also covers most of the total campaign ad spend.

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Prior to hypothesis testing, preprocessing of raw data removed the effect of outliers and confounding variables. By graphing box plots based on the amount of clicks for keyword-ad pairs, 190 ads with extreme click volume were removed, corresponding to 0.007% of the keyword records from the top sixteen ranks. Outliers were removed since their inclusion would significantly skew any statistical analysis, although a separate analysis on these high outliers would be fruitful future research.

Next, a log transformation of the data distribution was employed for all variables. The data is not multivariate normal; instead, it has a power law distribution. We transformed the data via the Box-Cox power transformation (Box and Cox, 1964) using ln(variable+1). After employing the transformation, data was plotted to check for normality. Data were successfully normalized, although distributions were skewed to the left (i.e., weighted toward lower cost-per-click, lower sales, lower number of orders, etc.), which is understandable given the type of data from SEA campaigns. Prior works have noted that the analysis of variance (ANOVA) method is robust to these deviations from normality (Lindman, 1974). Considering the validity of one way ANOVA, we compared means and variances for each of the two hypotheses. Because of the relatively large dataset, a conservative threshold of 0.01 was adopted. We implemented Tamhane's T2 test, which does not assume equal variances among the groups, for the post-hoc evaluation of specific group differences, with significance set at 0.01.

Click Potential (CP) Analysis

Table VII summarizes results in support of H1 (*There will be a significant difference in Click Potential based on ad rank.)*. Results of the one-way ANOVA test on CP indicate significant differences across ad ranks ($F(15) = 635.12$, $p < .01$). Based on the Tamhane's T2 test, CP differs significantly among all ad ranks. All pairwise comparisons are significantly different from each other ($p < .01$), with the higher ranked ad ranks generally having a higher RCP than the lower ad ranked. However, somewhat to our surprise, we did discover that the ad ranked in the number three position had higher RCP than the ad in the second ranked position.

--- Insert Table VII. ---

Conversion Potential (CvP) Analysis

Table VIII summarizes key findings supporting H2 (*There will be a significant difference in Conversion Potential based on ad rank.)*. The result of CvP comparisons using the one-way ANOVA show significant differences among ad ranks ($F(15) = 485.173$, $p < .01$). As indicated by the Tamhane's T2 test, click volume differs significantly among all ad ranks.

--- Insert Table VIII. ---

Interestingly, the majority of the significant difference in CvP was due to the change in CP. A follow-up pairwise comparison of CR among all 16 ad ranks indicated that only the topmost ad rank had a significantly higher CR than the other 15 ad ranks. The second and third ad ranks only showed significant differences as compared to the top 15 and top 8 ad ranks, respectively. There were no such significant differences among all the other ad ranks ($p > .01$, for each pairwise comparison). Generally, we conclude that the top three ad ranks have statistically significant higher Conversion Rates, while there is no difference in CR for ads in ranks 4 through

16. This would indicate, that once ads are of reasonable quality, traffic is the impactful variable on sales volume.

These findings highlight why a metric such as Conversion Potential is needed for decision making. Although the Conversion Rates are not significantly different for these ad ranks, once the effect of traffic is introduced, it is obvious, and as shown in the Conversion Potential metric, that the upper ad ranks are better overall for the performance of the keyword marketing effort.

Implications

To an extent, an advertising effort is what it measures. Poor metrics can lead to poor performance. However, if a metric is precise, accurate, and robust, it can provide keen insights into the overall effectiveness and efficiency of the marketing effort, enabling the business to make informed decisions. In other words, a metric can make the difference between success and failure in an advertising effort. We believe, and have shown both conceptually and empirically, that the combined metrics presented in this research are an improvement over metrics commonly utilized in the industry. They outperform the singular metrics that are currently industry standard.

Responding to the need for research about the lack of conceptualizations of SEA performance and combined metrics, as well as operationalization problems (Jafarzadeh *et al*., 2015; Katsikeas *et al.,* 2016; King *et al.,* 2015), this research bridges a gap between theory and practice, as one of the few academic works that presents not only theoretical constructs but validates them with actual advertising data. As a major contribution to the academic literature, our study formalizes Brooks' (2004a, 2004b) concept of Conversion Potential (CvP) for the evaluation and management of SEA campaigns, being one of the few research studies that contributes to the SEA metrics literature. CvP was evaluated using data from a real-world campaign, not an empirical evaluation of ad rank per se, but as an effort to enhance understanding about SEA performance (Agarwal *et al.,* 2011; Avanso and Karimi, 2015; Ghose and Yang, 2009; Liu *et al.,* 2009). Table IX demonstrates evidence of a reliable influence of ad rank as an optimization factor on Click Potential (CP) and CvP, to demonstrate the practical value of using such metrics within a SEA campaign performance framework.

--- Insert Table IX. ---

A vital aspect of understanding SEA performance involves CR and CvP comparisons when using optimization factors. In our case of using ad rank, the data revealed a dramatic drop from ad rank one to two. Among all 16 ad ranks, only the top two ad ranks exhibited profound differences in conversions. Thus, as a second contribution to the body of knowledge, this study found that, unlike the monotonic decreasing clicks, the Conversion Rates (CR) for ads placed after the second rank remained relatively stable, with all 14 ad ranks sharing roughly the same average CR. Thus, we can reasonably conclude that ad rank has only limited effect on final conversions after the first three ranks, given that the actual CR varied non-significantly across all ad ranks ranging from 4 to 16. However, there is conversion benefit, despite comments that CR does not vary by rank, of being in the top ad ranks when combined with the increase in traffic at these ad ranks, as indicated by the CvP for these ad ranks. Table IX illustrates that CvP dropped about 27%, due to the drastic reduction in the ad rank's CP. Thus, CR alone should not be used as a measure of the success of campaigns or ad ranks or ads, as traffic generation has a more meaningful impact on total revenue once CRs become stable among ad positions.

Theoretically, as illustrated in Figure II, this research provides preliminary evidence that CvP may be a more accurate measure of the impact of an ad's rank. Concerning Relative Click Potential (RCP), the trend line is generally linear with a sharp decrease from ad rank one to ad rank two and then another decrease to ad rank three. However, RCP then increases at ad rank four and remains stable through ad rank sixteen. With respect to Relative Conversion Potential (RCvP), the trend is curvilinear, with a fairly steep downward slope from ad ranks one to three and then a gentler downward slope from ad ranks four to eight, and ending with a near linear slope from ad ranks nine through sixteen.

--- Insert Figure II. ---

With respect to Table IX, there are two managerial implications that may help achieve optimal marketing outcomes. First, instead of evaluating clicks and conversions in isolation, this research shows the power of including CP and CvP to assess overall SEA performance. Evaluating site traffic and conversions simultaneously can advance the analysis by providing a much richer interpretation of the advertising data. In our case, the results showed a dramatic rise in CP between ad ranks two and three, in contrast to the overall decreasing pattern as indicated by the other ranks. This indicates that, after the decline in traffic at ad rank one to ad rank two, there is a spike in traffic at ad rank three, followed by a generally steady decrease in traffic from ad ranks four through sixteen. It is because of CP and CvP that these patterns can be observed.

Second, CP and CvP, appear to provide managers with a mechanism to mutually evaluate and make decisions about SEA campaigns, such as more effectively targeted bidding behavior and budget management. By including the CvP metric in the analysis, SEA managers may be able to make more informed decisions about campaign efficiency and progress. Understanding subtle changes in campaign performance can have profound impacts on an organization's bottom line and performance in the highly competitive online advertising industry.

Future Research and Limitations

We conclude that the conceptual framework offered by CvP is theoretically sound and managerially practical, but study limitations should be considered. First, the dataset comes from one company in one sector, retail. Although quite large both in terms of number of records and temporal span, further research with other companies and in other sectors is needed to ensure that the results can be generalized. Second, the dataset does not contain fields recording user's behavior with other channels, thus limiting the ability to analyze a user's omnichannel behavior and complete journey via the search results by tracking actions through other channels, such as phone or in-store purchases or via attribution modeling. We did, however, find relatively direct indications on user's purchasing intent within a single keyword query session by analyzing data from the advertiser's perspective.

While challenging to measure, it would be useful to explore other purchasing behaviors. An extension of this study would be relating CvP to financial metrics, such as return-on-advertising, in order to forecast patterns. Another avenue for future research is investigating other optimization factors besides ad rank that could also affect CvP, such as product price, type of query (Jerath, Ma, and Park, 2014), stage of the buying funnel (Jansen, Sobel, and Zhang, 2011), branding (Rutz and Bucklin, 2011), demographics (Jansen, Moore, and Carman, 2013), and search intent. While this study represents a step toward greater theoretical understanding, a future research challenge involves replicating and extending this work, for example through sophisticated modeling, to determine if the CvP metric works as expected.

Despite these limitations, the research has several strengths such as the large dataset, the lengthy period of data collection, the analysis of major SEA attributes, and the application of a theoretical construct to address search behavior, addressing a critical need in the literature. Along with formalizing the construct of CvP in the literature, this research employed a robust empirical analysis to instantiate CvP as a useful metric for overall account performance. The study provided evidence regarding how CvP impacts both campaign traffic (i.e., quantity) and sales (i.e., quality) in SEA, using the attribute of ad rank. The research presented here is a valuable contribution to the growing area of study in the SEA area of online marketing by integrating thought leadership from the practitioner community. As well as its profound academic value of formalizing key concepts, the research is of practical worth for advertisers currently engaged in SEA campaigns by providing insights on how to understand their own data via CvP. Leveraging the results of our research, advertisers can use CvP to assess both the effectiveness and efficiency perspectives. We believe our study inspires future researchers to continue exploring the growing area of SEA, building upon this work.

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Keyword	CTR = Clicks/Impressions	CR = Conversion/Clicks
A	100%	0%
B	80%	2.5%
C	30%	17%
D	4%	25%
E	1%	100%

Table I. Interpretation flaws with CTR and CR alone

Keyword	Impressions	Clicks	CTR = Clicks/Impressions	Conversions (# of Sales)	CR = Conversion/Clicks
A	100	100	100%	0	0%
B	100	80	80%	2	2.5%
C	100	30	30%	5	17%
D	100	4	4%	1	25%
E	100	1	1%	1	100%

Table II. Hypothetical data to illustrate a masking effect with CTR or CR alone

	Traffic Ratio	Sale Ratio
Traffic Ratio	Click-through-Rate (CTR)	
Sale Ratio		Conversion Rate (CR)

Table III. Matrix illustrating the lack of a metric that simultaneously measures both traffic and sales

	Traffic Ratio	Sale Ratio
Traffic Ratio	Click-through-Rate (CTR)	Conversion Potential (CvP)
Sale Ratio	Conversion Potential (CvP)	Conversion Rate (CR)

Table IV. Matrix illustrating the proposed metric of CvP

Campaign	Impressions	Relative Impressions	Clicks	CTR	CP	RCP	Conversions	CR	CvP	RCvP
F Baseline	100	---	100	100%	100%	---	20	20%	100%	---
G	90	90%	30	33.3%	29.97%	-70.03%	4	13%	3.90%	-96.1%
H	80	80%	10	12.5%	10.00%	-90.00%	1	10%	0.10%	-99.0%

Table V. An illustration of click potential (CP), relative click potential (RCP), conversion potential (CvP), and relative conversion potential (RCvP)

	Occurrence	Average per ad by day	Percentage of Overall Dataset
Impressions	403,868,723	70.61	95.45%
Clicks	13,227,492	2.31	99.57%
Advertising Cost	$847,397,224	$1.48	99.87%
Sales	$5,596,664,315	$ 9.78	99.54%
Orders	370,480	0.065	99.48%
Items	687,237	0.12	99.46%

Table VI. Cumulative statistics from the top sixteen ads ranks

Ad Rank	Click Potential (CP)	Relative Click Potential (RCP)	Average Number of Impressions	CTR	Change in CTR From 1st Ad Rank
1	100.0000%	---	61.1202	.0928	---
2	66.4281%	-33.57%	119.9303	.0539	-41.9181%
3	78.3054%	-21.69%	181.8403	.0417	-55.0647%
4	55.9611%	-44.04%	156.2295	.0323	-65.1940%
5	41.1827%	-58.82%	135.9430	.0257	-72.3060%
6	30.1280%	-69.87%	115.5875	.0215	-76.8319%
7	21.2774%	-78.72%	93.0717	.0182	-80.3879%
8	14.1709%	-85.83%	70.3922	.0160	-82.7586%
9	11.0378%	-88.96%	56.9634	.0151	-83.7284%
10	8.4450%	-91.56%	43.7833	.0149	-83.9440%
11	7.9011%	-92.10%	42.6729	.0142	-84.6983%
12	6.6229%	-93.38%	36.8290	.0142	-84.6983%
13	5.7727%	-94.23%	33.6999	.0134	-85.5603%
14	4.3799%	-95.62%	26.4894	.0127	-86.3147%
15	3.9368%	-96.06%	25.5058	.0124	-86.6379%
16	3.3048%	-96.70%	21.5285	.0125	-86.5302%

Note: All ad ranks were significantly different in CP using Tamhane's T2 post hoc test results at $p < 0.01$.

Table VII. CP and RCP by ad rank, with associated impression and CTR data

Ad Rank	*Conversion Potential (CvP)	Relative Conversion Potential (RCvP)	Conversion Rate (CR)	% Change in Mean Conversion Rate from 1st Ad Rank
1	100.0000%	---	0.0266	---
2	32.2151%	-67.7849%	0.0129	-51.5759%
3	27.6718%	-72.3282%	0.0094	-64.5739%
4	17.0408%	-82.9592%	0.0081	-69.6121%
5	12.6954%	-87.3046%	0.0082	-69.1254%
6	8.6080%	-91.3920%	0.0076	-71.4806%
7	5.6793%	-94.3207%	0.0071	-73.4404%
8	3.9955%	-96.0045%	0.0075	-71.7752%
9	3.3611%	-96.6389%	0.0081	-69.5386%
10	2.5716%	-97.4284%	0.0081	-69.5421%
11	2.1980%	-97.8020%	0.0074	-72.0402%
12	1.9918%	-98.0082%	0.0080	-69.7969%
13	1.7579%	-98.2421%	0.0081	-69.4486%
14	1.1691%	-98.8309%	0.0071	-73.5318%
15	1.1396%	-98.8604%	0.0077	-70.9358%
16	0.9939%	-99.0061%	0.0080	-70.0267%

Table VIII. CvP and RCvP by ad rank, with associated conversion metrics

*All ad ranks significantly different in conversion potential using Tamhane's T2 post hoc test results at $p < 0.01$.

Ad Rank	Click Potential (CP)	Relative Click Potential (RCP)	Conversion Potential (CvP)	Relative Conversion Potential (RCvP)
1	100.0000%	---	100.0000%	---
2	66.4281%	-48.4962%	32.2151%	-67.7849%
3	78.3054%	-35.3383%	27.6718%	-72.3282%
4	55.9611%	-30.4511%	17.0408%	-82.9592%
5	41.1827%	-30.8271%	12.6954%	-87.3046%
6	30.1280%	-28.5714%	8.6080%	-91.3920%
7	21.2774%	-26.6917%	5.6793%	-94.3207%
8	14.1709%	-28.1955%	3.9955%	-96.0045%
9	11.0378%	-30.4511%	3.3611%	-96.6389%
10	8.4450%	-30.4511%	2.5716%	-97.4284%
11	7.9011%	-27.8195%	2.1980%	-97.8020%
12	6.6229%	-30.0752%	1.9918%	-98.0082%
13	5.7727%	-30.4511%	1.7579%	-98.2421%
14	4.3799%	-26.6917%	1.1691%	-98.8309%
15	3.9368%	-28.9474%	1.1396%	-98.8604%
16	3.3048%	-30.0752%	0.9939%	-99.0061%

Table IX. Absolute and relative metrics for CP and CvP by ad rank

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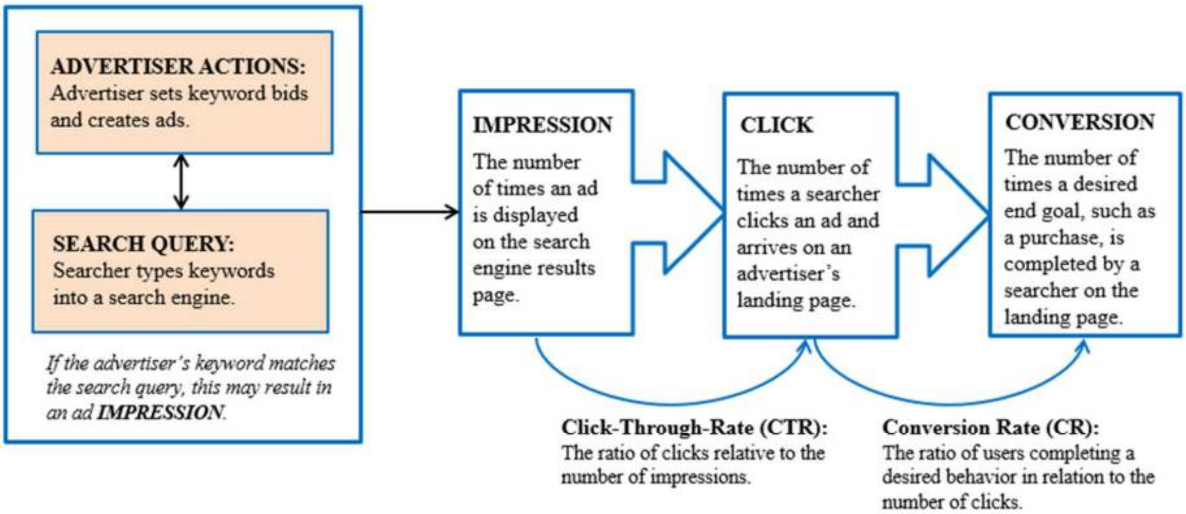

Figure I: The SEA process

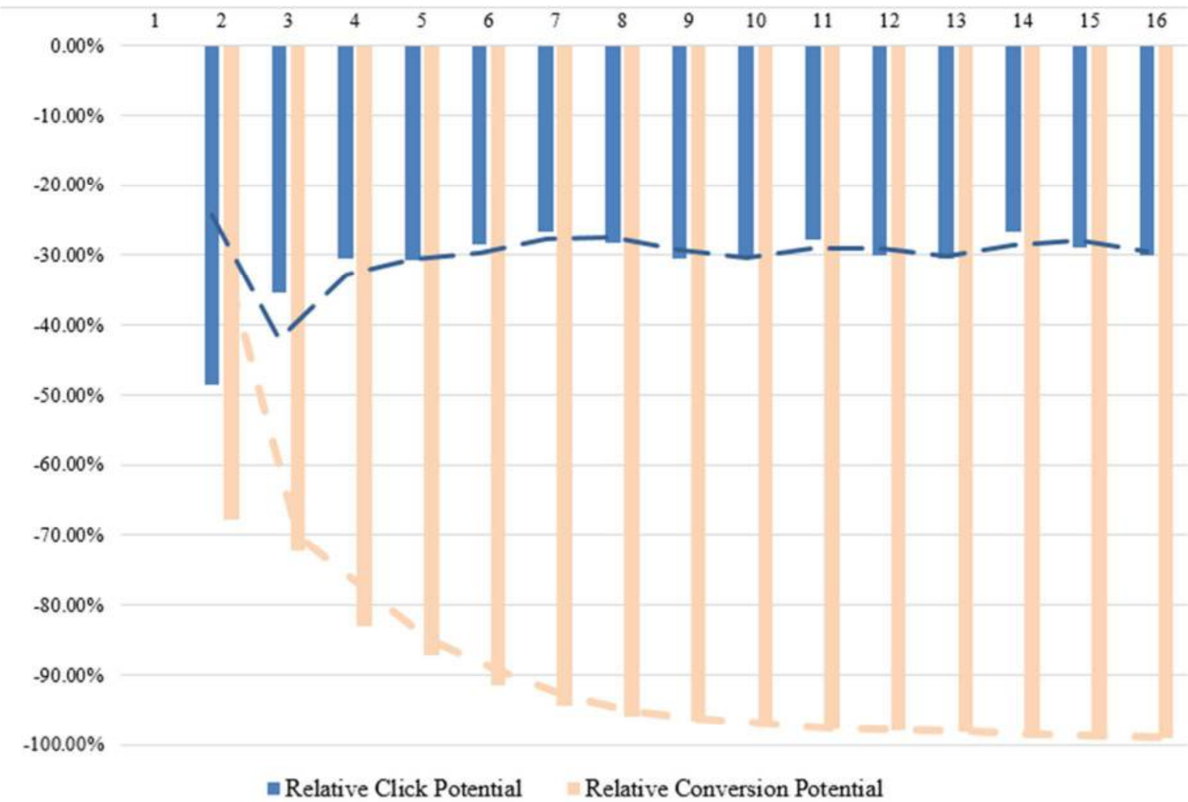

Figure II. RCP and RCvP with moving average trend lines