Impact of Digital Marketing on User Acquisition

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1 ABSTRACT

As digital platforms rapidly gain users, it is more important than ever for companies to shift their marketing efforts towards digital marketing. We conducted a case study on the marketing effort of a small, low-funded mobile health application called "nOCD."

2 Introduction

Marketing can be defined as a form of communication between a company and its potential customers with the goal of selling the company's product or service to the customer. People have always had something to sell; figuring out how to sell it is "marketing." Ever since the printing press was invented in 1440, "outbound marketing" has been the practice of choice: companies send out mass advertisements that interrupt consumers to talk about their product (Wainwright, 2012). As technology improved, new mediums for marketing arose – magazines (1730s), posters (1830s), billboards (1860s), radio (1920s), television (1940s), and telephones (1940s). Outbound marketing continued to be the marketing practice of choice: first through posted advertisements, then through telemarketing. It is very difficult to measure the returns of outbound marketing – it costs x amount of money to print or air an ad, but it is tough to figure out exactly how many people viewed the ad or were persuaded by it.

Then, the personal computer entered many households. By 1997, search engines were widely used. These search engines were a powerful marketing tool because they put the power back into the hands of the consumers: consumers can decide what they want to search. The first social media sites were launched in the early 2000s. Many grew rapidly. The turn of the century marked the entrance of firms into the age of "inbound marketing" – a marketing practice with an emphasis on "information sharing, user-centered design, and collaboration" (Wainwright, 2012). Instead of a company talking at its consumers, the consumers engaged with a brand. As inbound marketing rapidly gained momentum, outbound marketing lost momentum. More and more people joined social media, and more and more people joined the "National Do Not Call Registry."

In 2012, there were over 200 million Americans on the Do Not Call List, showing the newfound distaste for the once successful telemarketing. The amount of active users on Facebook has been growing rapidly from 100 million in 2008 to almost 2 billion in 2016 (Facebook, 2017).

While the return on investment, or ROI, of outbound marketing practices is difficult to measure, the ROI of inbound marketing practices can be calculated. Instead of attempting to make a quick sale, a company should try to develop a relationship with potential customers to cultivate warm prospects out of cold leads. Every aspect of inbound marketing can be tracked and analyzed if the company employs the right technology. It is possible to see how each digital media marketing practice impacts new user acquisition. Some researchers have attempted to measure the impact of inbound marketing practices (Reza, 1998) (Hoffman & Fodor, 2010), and even suggested that we introduce a new academic major called "digital marketing" (Wymbs, 2011). The existing research largely focuses on sizable companies. This paper focuses on measuring the ROI of the marketing practices of nOCD, a company that is in an earlier stage of growth.

nOCD is a mobile application that assists in the treatment of Obsessive Compulsive Disorder (OCD). The nOCD team has not raised a "Series A" round of funding, so they primarily rely on a digital user acquisition strategy to grow the business. If the digital marketing strategy transitions to a solid word-of-mouth user acquisition strategy, the team's efforts spent acquiring one user can translate into acquiring multiple. Therefore, it is important to understand which marketing channels drive user acquisition.

3 Literature Review

Reza Kiani (1998) recognized the marketing paradigm shift from outbound marketing to inbound marketing. Although this paper was written prior to the computer's prevalence in society, Reza Kiani realized that digital media created a two-way communication medium. Instead of companies marketing directly towards consumers, there was communication: company to consumer, consumer to company, company to company, and consumer to consumer. The nOCD team hopes to increase the communication between current users and potential users of their product, and thus spread knowledge of their application via word-of-mouth.

Instead of measuring return on investment in terms of customer response, Hoffman & Fodor (2010) emphasize that companies should instead measure the social media "investments" that customers make in the marketer's company, including number of blog or website visits, time spent using the application, number of Facebook posts or Tweets about the brand, and more. These should all be constantly tracked and analyzed so a company can detect change in awareness levels or word-of-mouth communication over time. Hoffman & Fodor describe the importance of digital marketing strategies.

> Traditional media measurement seems almost quaint in today's dynamic and increasingly complex media environment. Marketers are

> struggling with social media measurement partly because the frameworks are still largely driven by 'reach and frequency' and are all ill-suited to the interactive media environment.

Managers are trying to convert social media presence into sales as quickly as possible, while they should realize that forming online relationships with customers requires time and attention. If a company can create a medium in which customers chat with representatives from a company, they can develop long-term relationships. Customers control the time they devote to the digital sphere. If they are spending time interacting with a company's social media accounts, that company has done something to grab their attention. By allowing users to create different groups and pages, Facebook naturally forms ultra-targeted marketing channels where consumers can socialize with each other. Twitter and Instagram are not as targeted, but they are still useful digital marketing platforms. Hoffman and Fodor list some relevant metrics for measuring the ROI of various social media applications. These examples helped us to frame our study. Hoffman & Fodor also illustrate cases in which companies launched marketing campaigns and the consumers responded on social media. One example is summarized below.

> **Case Study: Motrin (2008)**
>
> Johnson & Johnson launched a video campaign featuring mothers wearing babies in a body sling, with the message that wearing a baby is tough on a mother's body, so she should use Motrin. Many mothers took offense – saying that the advertisement was condescending and exploitive. A digital media movement began in which mothers criticized the brand on Twitter and blogs. "Motrin Moms" quickly became a trending topic. Motrin did not respond right away, and perhaps was not even aware that this movement was taking place. They responded days later, after the digital media movement was covered by mainstream media.

Dave Chaffey's "Global social media research summary (2016)" gathers current social media statistics. The graphs and charts that Chaffey includes paint the picture that Facebook is the current social media giant, but other social media applications will grow at a faster rate. The graph titled "Age 18-34 Digital Audience Penetration vs. Engagement of Leading Social Networks" shows that Facebook reaches almost 100% of 18-34 year-olds in the US. In addition, Facebook is currently at 63% penetration (percent of potential users reached), while Twitter and Instagram are at 22% and 27% penetration, respectively. If companies invest their time and resources into marketing these mediums, it will pay off as the mediums gain users. Another graph shows that almost 75% of adults are on social media, compared to 50% in 2009.

4 nOCD's Strategy

It is essential to have an effective user acquisition strategy to secure future investments. Currently, the nOCD team uses multiple Software Development

Kits (SDKs) to obtain data, including Branch.io. Branch.io generates "deep links" to measure the efficacy of each digital marketing strategy (see section 4.1). nOCD also uses Slack, a remote communication platform, to connect employees that work all over the world. Through this RCP, employees share thoughts, itineraries, and documents.

In addition to using SDKs, the team also uses multiple web-based analytics and communication platforms. Through these platforms, the team can log and then analyze different variables such as: users acquired in a day, hours spent interacting on social media, followers obtained on a given social media platform, impressions made on a given platform, many more. These variables help the nOCD team understand their digital marketing strategy. In total, the team has over 20,000 followers across Facebook, Instagram, and Twitter, making the sample large enough for the team to make data-driven conclusions.

As a hypothesis, the team designed their marketing strategy around the following notion: growing a large "OCD awareness movement" on social media will generate enough buzz to encourage people to download the application. Also, having a strong Forum presence, Search Engine Optimization score, and Newsletter will create a scalable digital marketing strategy.

4.1 Deep Links

Deep links are custom links that connect potential online users directly to a specific product. Most links on the web are deep links (branch.io). When clicked, a deep link will take the user to content. nOCD uses deep links to simplify the download process of an app for the user and trace which marketing channel led to that download. Deep links can trace user activity – leading to a positive user experience, and ultimately, more installs (BI Intelligence, 2016). Deep links can be placed in various mediums, including websites, emails, text messages, and within applications.

4.2 Newsletters

The nOCD team also collects data from its newsletters using the service Mailchimp. The team sends a newsletter twice a week to two different audiences: clinicians and nOCD patients. Inside each email, the team implements multiple Branch.io deep links, leading potential users directly to the store. The purpose of the newsletter is to reach clinicians who will download the app and recommend it to their patients. As the nOCD Newsletter's audience grows, the team hopes to increase the rate of user acquisition.

4.3 Forums

An internet forum is an online message-board in which users hold conversations. Many of these message-boards are visible to the public through search engines. The nOCD team also tracks the deep links that are posted on forums like Reddit.

4.4 Search Engine Optimization (SEO)

Search engine optimization is "the art, craft, and science of driving web traffic to websites" (Davis, 2006). Search engines, like Google, have algorithms that funnel highly targeted users directly to specific websites based on the keywords searched. Companies want to appear as close to the top of the search engine results as possible for relevant searches. Companies employ many strategies to increase the frequency of appearing in search results.

It is important for a company to have a positive public image, or positive Public Relations (PR). Firms can improve their SEO by backlinking their site to quality websites, since search engines find that a high number of backlinks is associated with a high amount of credibility. For example, if the nOCD website is linked on an article from a credible news source like ABCnews, Google will attribute keywords from the article with the nOCD website. With PR, firms can effectively raise their SEO score and thus get found more easily by potential consumers.

4.5 Social Media

Social media websites have been rapidly growing. With a combined active user base of over two billion people (Social Media Statistics & Facts, 2016), it is very important for a company to spend time and effort marketing through these mediums. The nOCD team spends many hours each day on each of these mediums.

5 Data

The nOCD team collects over sixty different variables each day in order to track and analyze the impact of various digital marketing strategies. Over the course of the 108 daily observations logged by the nOCD team, the product's quality has not improved or worsened, based on the product's event data. Any and all growth has been a result of the team's marketing efforts. On Instagram, Facebook and Twitter, the team collects "click" data, "effort" data, and "post" data. By collecting these variables, the nOCD team hopes to understand which actions on social media most effectively drive impressions and the impact that these impressions have on acquiring new users. Learning the tactics that best drive impressions, and thus users, is crucial for any early stage startup with little capital. The data presented in the following sections are the training data.

5.1 Click Data

The nOCD team collects data on how many people click the links that can be found on Facebook, Instagram, Twitter, Reddit, the nOCD website, and in their newsletter. Because of deep links, the team can see exactly which medium each link click comes from.

VARIABLE	New Users Acquired	Newsletter Clicks	Facebook Clicks	Instagram Clicks	Twitter Clicks	Reddit Clicks	nOCD Clicks
AVERAGE	18.32	5.50	4.13	4.55	1.81	1.81	10.75
MAX	64.00	101.00	111.00	49.00	16.00	54.00	29.00
MIN	4.00	0.00	0.00	0.00	0.00	0.00	1.00
STANDARD DEVIATION	9.55	15.32	11.63	5.60	2.75	7.11	4.90

Table 1: Summary Statistics: Daily Deep Link Clicks

5.2 Effort Data

The team also collects data on the employee-side to measure the effort of each employee. They track how many hours each team member spends on Facebook, Instagram, and Twitter each day, recording how much time is spent interacting with users and performing searches.

VARIABLE	Facebook Hours	Twitter Hours	Instagram Hours	New Users Acquired
AVERAGE	0.35	1.90	3.17	18.32
MAX	4.00	6.25	11.00	64.00
MIN	0.00	0.00	0.00	4.00
STANDARD DEVIATION	0.77	1.74	2.73	9.55

Table 2: Summary Statistics: Individual Hours

5.3 Post Data

Additionally, the team collects data on how many posts, paid posts, and direct messages each team member sends out. The team members will either post original content themselves, or pay Facebook or Instagram to put it in front of a larger audience.

VARIABLE	Twitter Normal Posts	Facebook Normal Posts	Instagram Normal Posts	Facebook Paid Posts	Instagram Paid Posts	New Users Acquired
AVERAGE	7.20	0.59	0.65	0.08	0.13	18.32
MAX	47.00	6.00	3.00	1.00	1.00	64.00
MIN	0.00	0.00	0.00	0.00	0.00	4.00
STANDARD DEVIATION	8.37	0.90	0.62	0.28	0.23	9.55

Table 3: Summary Statistics: Individual Actions

6 Methods

Given that we are using time series data, we must ensure that the data are stationary. Using non-stationary time series data in regression analysis can lead to spurious regressions, which must be avoided in order to a draw proper inference. We performed several unit root tests to determine stationarity: the

Augmented Dickey-Fuller (ADF) test, the Phillips-Peron (PP) test, and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test.

ADF and PP both test the null hypothesis that a unit root is present in the data sample. PP has the advantage of being a non-parametric test, and is robust to autocorrelation and heteroskedasticity of the test equation. However, PP draws from asymptotic theory, and should only be used with sufficiently large samples. Given that we have 108 samples at the time of writing, it is unclear if PP is apt in this case, but we include it nonetheless. Additionally, both PP and ADF are sensitive to structural breaks and have poor small sample power.

The inclusion of KPSS helps to balance the drawbacks of ADF and PP. KPSS flips the null hypothesis on its head and tests for the hypothesis that the sample lacks a unit root (or is trend stationary). This allows us to make a more informed statement about the probability that our variables are stationary. We find that all the variables included in our analysis did not show signs of non-stationarity via our various tests.

We estimate all our models using negative binomial regression and quasi-Poisson regression. Negative binomial regression is a modeling technique specifically designed to work with count data. This is appropriate, given that our primary variable of interest, new users acquired, is by its nature always a positive integer. Negative binomial regression is a generalization of the Poisson regression. Poisson regressions require the dependent variable's variance to be equal to its mean. However, our data are over-dispersed, meaning that the variance is greater than the mean, which suggests that negative binomial regression is more appropriate.

We also estimate our models using quasi-Poisson regression, another common approach to over-dispersed count data. Quasi-Poisson regression uses quasi-likelihoods estimation, maximum likelihood likelihood estimations when the underlying distributions are misspecified. We include results from both regression techniques because it is unclear which is the best specification for our variance structure. Negative binomial regression assumes that variance is a quadratic function of the mean, while quasi-Poisson assumes that it is a linear function.

For all of our model specifications, we use Hubey-White standard errors to correct for the problem of heteroskedacitiy in our residuals. While this approach has the benefit of producing heteroskedacity-consistent standard errors, it has a drawback. The estimator is only asymptotically consistent, and it is not obvious that we have enough data. Additionally this leaves our model vulnerable to autocorrelation of our residuals. However, we find in our analysis that none of our regressions display autocorrelated residuals, which we test for using the Ljung-Box test.

After tweaking and adjusting our model specification to a high degree, it is necessary to ensure that we have not over-fit our model. In order to make sure that we do not torture the data, we will split the dataset into training and testing sets. This will allow us to validate our test specification by ensuring that it holds up in out-of-sample tests. Out of sample testing reveals that all relationships discussed below are consistent, though some become insignificant due to smaller size of the testing set.

Finally, we must assess our model for endogeneity. Given the complex nature of advertising and the limitations of our dataset, it is possible that endogeneity is present in our model due to omitted variable bias. Simultaneity and reverse causality are also threats: desirable or deleterious user acquisition rates may affect advertising efforts by the company. Additionally, since we include lagged dependent regressors, autocorrelation of the error term would also be fatal. Measurement error may be possible if actions leak from one time period to another due to inconsistent or inaccurate record keeping.

7 Results

In this section we analyze four different aspects of new user acquisition. First, we observe the autocorrelation structure of new users acquired, which informs the rest of our models. Following this, we test to determine which mediums drive the most traffic towards user acquisition. Next, we attempt to determine how the time spent on social media outreach affects user acquisition. Lastly, we attempt to determine how different advertising actions effect user acquisition.

7.1 New Users Acquired

Before beginning our analysis, we examine new users acquired for autocorrelation. As can be seen in Table 4, we detect first order autocorrelation as well as first order partial correlation. Based on this, we choose to include one autoregressive lagged term in the rest of our models. By doing this, we no longer observe autocorrelation among the residuals in the remainder of our regressions.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|** |	.|** |	1	0.280	0.280	8.6929	0.003
.|. |	*|. |	2	0.005	−0.079	8.6960	0.013
*|. |	*|. |	3	−0.193	−0.189	12.921	0.005
.|. |	.|* |	4	−0.002	0.120	12.921	0.012
.|* |	.|* |	5	0.114	0.090	14.421	0.013
.|* |	.|* |	6	0.183	0.094	18.342	0.005
.|. |	.|. |	7	0.039	−0.026	18.525	0.010
.|. |	.|* |	8	0.045	0.089	18.769	0.016
*|. |	*|. |	9	−0.096	−0.101	19.885	0.019
*|. |	*|. |	10	−0.085	−0.066	20.762	0.023

Table 4: New Users Acquired Correlogram

7.2 Traffic Analysis

Here, we wish to determine which mediums drive the most traffic toward new user acquisition. As discussed in the data section, deep linking allows us to monitor which medium directs an individual to a certain page, like the sign-up page. We regress the number of clicks from a given source against the number of new users acquired in a given day. We include deep link clicks from the sources listed in the regressions given in Figure 1. We excluded lagged click regressors from our model since we determined by testing that none of the regressors Granger caused new users acquired at two lags.

As can be seen in Figure 1 the main sources of effective traffic are the Newsletter, Facebook, and the nOCD Website. As expected, none of the coefficients are robustly significantly negative. We include an AR(1) term to provide a better model fit, though it is not included in the regression table as it provides no economic interpretation in our case.

	Negative Binomial Regression	Quasi-Possion Regression
Constant	2.286***	2.383***
	(0.090)	(0.071)
Newsletter Clicks	0.009***	0.01***
	(0.002)	(0.001)
Facebook Clicks	0.008***	0.008***
	(0.002)	(0.002)
Instagram Clicks	0.000	-0.008*
	(0.006)	(0.004)
Twitter Clicks	0.011	0.014*
	(0.011)	(0.008)
Reddit Clicks	-0.003	-0.003
	(0.004)	(0.003)
nOCD Website Clicks	0.030***	0.028***
	(0.007)	(0.005)
R-squared	0.596	0.640
Adjusted R-squared	0.567	0.610

Standard errors are reported in parentheses.
*,**,*** indicates significance at 90%, 95%, and 99% level, respectivly

Figure 1: New Users Acquired by Deep Link Clicks

We hypothesize that the newsletter and nOCD website clicks are significant in terms of downloads, because individuals who click on those links are more likely to be highly interested consumers rather than relatively randomly targeted individuals from social media sources. We additionally hypothesize that Facebook clicks are significant because nOCD only recently began recruiting on Facebook and thus are more likely to catch the notice of individuals who have not yet heard of nOCD.

7.3 Hours Spent

In this section we wish to determine if time spent on one platform is more effective than time spent on others. As discussed in the data section, we have employee time spent interacting on social media for nOCD's Facebook, Instagram and Twitter accounts.

First, we wish to establish if time spent interacting on social media accounts actually affects new user acquired outcomes. To test this hypothesis we sum time spent on all social media accounts to generate the variable "total hours'.' Via a Granger causality test we find that we cannot reject the null that total hours granger causes new users acquired at 1 lag. As such, we included a lagged variable in our regression to test the possibility of lagged effects.

In Figure 2 we present the results from the aforementioned regression. We determine that hours spent on social media is significant on the day in question, but lagged effects are largely insignificant.

	Negative Binomial Regression	Quasi-Possion Regression
Constant	2.458***	2.506***
	(0.100)	(0.088)
Total Hours	0.03***	0.028**
	(0.011)	(0.011)
Total Hours(-1)	0.006	0.005
	(0.011)	(0.010)
New Users Aquired(-1)	0.013***	0.012***
	(0.005)	(0.004)
R-squared	0.111	0.119
Adjusted R-squared	0.085	0.094

Standard errors are reported in parentheses.

*,**,*** indicates significance at 90%, 95%, and 99% level, respectivly

Figure 2: New Users Acquired by Total Hours

In our next regression we examine the effects of hours spent on individual platforms. As informed by the previous model, we do not include lagged regressors for the individual regressors, given that their sum is jointly insignificant when lagged. The results from this regression are presented in Figure 3

	Negative Binomial Regression	Quasi-Possion Regression
Constant	2.465***	2.513***
	(0.101)	(0.087)
Facebook Hours	0.054	0.048
	(0.051)	(0.048)
Twitter Hours	0.047*	0.038
	(0.028)	(0.026)
Instagram Hours	0.025	0.026
	(0.019)	(0.019)
New Users Aquired(-1)	0.013***	0.012***
	(0.005)	(0.004)
R-squared	0.108649	0.1191
Adjusted R-squared	0.073694	0.084555

Standard errors are reported in parentheses.

*,**,*** indicates significance at 90%, 95%, and 99% level, respectivly

Figure 3: New Users Acquired by Individual Hours

We find that none of the individual regressors are significant in both the Negative Binomial regression and the quasi-Poisson regression. However, Twitter hours are significant at a 10% level in the Negative Binomial regression. The results suggest that none of the effects are significantly different from zero, or from each other. These two regressions together suggest that while time spent interacting with consumers on social media is effective in driving daily user acquisition, it does not seem to have lasting effects and is furthermore not qualitatively different among Facebook, Twitter and Instagram.

7.4 Actions Taken

Next we provide analysis of how actions on different social media platforms effect user actions. We begin by collecting the action measurements into totals. As discussed in the data section we have three action types: normal posts, paid posts and direct messages. Normal posts occur on Facebook, Instagram and Twitter, while paid posts only occur on Instagram and Facebook. Direct messages only occur on Twitter and Instagram.

We present the results from the totals regression in Figure 4. We find that normal and paid posts are both significantly positive, while direct messages do not have a significant relationship with new users acquired. We also find that paid posts are significantly greater than normal posts, which is encouraging given the cost.

	Negative Binomial Regression	Quasi-Possion Regression
Constant	2.611***	2.654***
	(0.097)	(0.086)
Normal Posts	0.011**	0.01**
	(0.005)	(0.005)
Paid Posts	0.276**	0.259**
	(0.125)	(0.121)
Direct Messages	-0.026	-0.021
	0.016	0.014
New Users Aquired(-1)	0.012**	0.009**
	(0.005)	(0.004)
R-squared	0.105	0.121
Adjusted R-squared	0.069	0.086

Standard errors are reported in parentheses.
*,**,*** indicates significance at 90%, 95%, and 99% level, respectivly

Figure 4: New Users Acquired by Total Actions

Next, we wish to determine the effectiveness of normal and paid posts among the different social media platforms. We present the results from the regression in Figure 5. We find that Instagram is the only site that has significantly positive posting effects robust to both regression techniques. This suggests that the social media push on Instagram is the most effective, and nOCD should either focus on that platform, or shore up its efforts on the others.

8 Conclusion

After analyzing the statistically significant results related to "Branch Link Clicks" and "Effort Exerted on Social Media," it is evident that the nOCD team's most effective new user acquisition strategies are driven by channels created from targeted impressions within the OCD community.

In the "Branch Link Click" test, the dependent variable: "New Users Acquired," expressed positive correlation with the explanatory variable's "Facebook Clicks," "Website Clicks," and "Newsletter Clicks." Each of the explanatory variables was derived from ultra-targeted impressions within the OCD community. As a result of connecting with a highly-targeted audience on different pages and groups, the nOCD team's Facebook account was able to drive more

	Negative Binomial Regression	Quasi-Possion Regression
Constant	2.513***	2.565***
	(0.116)	(0.099)
Twitter Normal Post	0.009*	0.008
	(0.005)	(0.005)
Facebook Nomral Post	-0.057	-0.056
	(0.052)	(0.053)
Instagram Normal Post	0.186**	0.173**
	(0.082)	(0.077)
Facebook Paid Post	0.265	0.263
	(0.209)	(0.210)
Instagram Paid Post	0.296**	0.282**
	(0.132)	(0.127)
New Users Aquired(-1)	0.011**	0.009**
	(0.005)	(0.004)
R-squared	0.124	0.139
Adjusted R-squared	0.071	0.086

Standard errors are reported in parentheses.

*,**,*** indicates significance at 90%, 95%, and 99% level, respectivly

Figure 5: New Users Acquired by Individual Actions

new users than any other social media platform. Instagram, surprisingly, showed inconclusive results. However, there is not enough information to claim that Instagram is ineffective. In addition to the social media accounts, the nOCD newsletter used outbound marketing tactics to reach both a targeted audience of OCD patients looking to improve their condition and clinicians who treat OCD and other anxiety disorders. The channel was designed by the nOCD team to drive impressions using highly vivid content, and it was successful. In addition to the use of a website and newsletter, outbound marketing techniques, company affiliated websites often drive new users through Search Engine Optimization, a widespread inbound marketing tactic.

The “Effort on Social Media” test differed from the “Branch Link Clicks” test since it highlighted correlation of effort on new users acquired. Effort on Twitter strongly correlated with “New Users Acquired” since Twitter’s user experience design is centered around the “retweet,” adding a multiplier effect to many interactions. Although the impressions are not ultra-targeted, the retweet multiplier effect on Twitter increases the probability of reaching more people, who could be within a target market.

Given the results, early-stage startups with limited funds should focus on building an influential Facebook page, enhancing their website's SEO, sending ultra-targeted newsletters, and creating interactions on Twitter. This approach will help early stage start-ups effectively reach their target market, which will give them the sample size and funds necessary to find Product-Market Fit.