Global Journal of Management and Business Research: E Marketing
Volume 20 Issue 3 Version 1.0 Year 2020
Type: Double Blind Peer Reviewed International Research Journal
Publisher: Global Journals
Online ISSN: 2249-4588 & Print ISSN: 0975-5853

Linkedin, Quantitative Analysis to Examine Members' Behavior and Motivations

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The LinkedIn networking social media plat form is used by 92% of Fortune 500 companies, followed by the two rivals Twitter (88%), and Facebook (85%), 99firms (2019). Despite experiencing significant growth in LinkedIn's membership, the company has not been able to grow its monthly active users beyond 25%, a figure that is relatively low compared to other popular social media like Facebook and Twitter. The small percentage of monthly active users is a thoughtful concern for LinkedIn as it would discourage future growth.

GJMBR-E Classification: JEL Code: M39

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Mariana Hu [α] & Magdy M. Hussein, PhD [σ]

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I. Introduction

One could not imagine life without Facebook status updates, following celebrities' Tweets, sharing funny YouTube videos, and connecting to recruiters on LinkedIn. With an ever-growing number of users and extraordinary engagement power, social media is nowadays one of the most popular Internet activities. In the United States, 81% of the population use social media and spend 3.6 hours per week on social networks via smartphone, 53 minutes via PC, and 50 minutes via tablet devices Number of social media, n. d. There is no doubt that social media had become an integral part of our lives.

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For businesses, this phenomenon has reshaped marketing and become a fundamental core element of business strategy. As a powerful marketing tool, social media provides an operative channel to increase brand awareness, promote products, engage with millions of potential customers, and generate leads. More and more businesses invest in social media advertising, resulting in worldwide spend doubling from USD 16 billion in 2014 to USD 31 billion in 2016. The US is by far the largest social media advertising market, with more than USD 9.4 billion in 2015 "Statistics and facts", (n.d.)

Social media's business success highly depends on its popularity, as measured in terms of active members rather than total registered members. Active members are more engaged, and by frequently logging in to the platform, they are more likely to see the advertisements, interact with other users, and generate data that is useful to businesses. Active members, therefore, allow social networks to monetize their services more effectively. As the lifeblood that powers their billion-dollar business models, active members are a significant indicator of social media success and a top priority for social media companies aiming to achieve future growth (Tonner, 2016).One commonly used metric for popularity is the monthly active users (MAU), which is the number of unique users for 30 days.

Facebook, a social network focusing on connections between friends and family, is currently the market leader in terms of reach and scope with two billion MAU and year by year 18% increase "Most famous", (n.d). Facebook is the most used social network for marketing purposes and is considered by the majority of marketers as the single most important social platform for their business. Facebook's popularity among marketers has a direct impact on its total revenue: it has the highest total revenue, advertising being the main source, and it has the highest Revenue Per Visit (RPV) in the industry. For every visit on Facebook, the company amounts to 1.25 U.S. dollars. Pinterest has the second-highest RPV – 0.74 U.S. dollars "Statistics and facts", (n.d.). Facebook is, therefore, an ideal example of a highly engaging social network that has leveraged its popularity to achieve impressive business success.

Conversely, LinkedIn, a social network connecting businesses and professionals suffers from low user engagement. Despite significant growth in memberships, LinkedIn has been unable to increase its MAU beyond the 25% mark since the second quarter of 2015 (Yeung, 2016). With 106 million MAU, LinkedIn lags way behind Facebook, WhatsApp, Instagram, and Twitter. LinkedIn ranks number 19 in terms of MAU, among other social media platforms. (Global social media ranking 2017, n.d.). Citing the *Financial Times*:

"When other social networks such as Facebook and Snap chat are beginning to put more weight on how many users open the app every day, or how many minutes they spend on the network, LinkedIn has been searching for new ways to get users to return at least once a month." (Kuchler, 2016).

LinkedIn has three main sources of revenue: the leading one is Talent Solutions, which allows recruiters to reach out to LinkedIn members as potential job candidates; the second one is marketing solutions; and the more active members make these services more valuable to recruiters, business and members.

As confirmed by various sources, low user engagement is a major concern for LinkedIn's future business growth. For example, the *Financial Times* recognized that improving user engagement on the platform is central to improve the quality of data, which in turn will increase revenue from Talent Solutions and advertising. Other sources have also expressed its concern about LinkedIn's low user engagement. During *LinkedIn's Q4 2015 Results Presentation*, the company itself acknowledged that the limited growth in active users could be a hurdle to its future monetization efforts (Team, 2016). Furthermore, a Tech Crunch article attributed LinkedIn's low user engagement as one factor driving the poor growth forecasts that led to LinkedIn shares dropping 43% in February of 2016. This source added that LinkedIn's current business model inhibits user engagement in its platform: by focusing on sales and recruiting, and showing interruptive advertising, LinkedIn discourages users from logging onto the platform, which in turn makes the product less useful for recruiters. To regain investors' trust, LinkedIn must change its strategy to encourage better user behavior (Kimmelman, 2016).

LinkedIn was acquired by Microsoft for USD 26 billion in December of 2016, making it the largest acquisition in the high tech industry. This study aims at identifying factors that drive higher user activity on LinkedIn. The findings will help LinkedIn develop strategies to make its platform more engaging, which in turn will allow it to monetize its services more effectively and achieve higher revenue.

The objectives of this study are:

- Understanding the focal motivations for using LinkedIn
- Understanding the effect of demographic and behavioral factors on member login frequency
- Assessing the effect of motivations for use and satisfaction with LinkedIn on member login frequency
- Identifying the factors that could drive higher login frequency
- The research questions to be answered are:
- How do demographic and behavioral factors affect member login frequency?
- What is LinkedIn members' key motivation for using the platform?
- Do LinkedIn members with more motivations login more frequently?
- Do LinkedIn members who are more satisfied with LinkedIn login more frequently?

This study will aim to prove the following five hypotheses:

— Frequency of login to LinkedIn varies according to demographic factors such as age, gender, level of education and occupation;

— Members who access LinkedIn via both computer and mobile application channels login more frequently than members who login via the computer or mobile application alone;

— Frequency of login to LinkedIn varies according to attitudes towards career development;

— LinkedIn members' main motivation to use the platform is job search;

— LinkedIn members who are more motivated to use LinkedIn login more frequently

II. Literature Review

A review of existing literature reveals different approaches used to examine the consumers' motivations to use social media. Archambault and Grudin performed a longitudinal study to analyze social media use from 2008 to 2011. Their subjects of study consisted of a random sample of Microsoft employees. Among the aspects examined were the four basic attitudes towards social media use: for fun, for personal socializing and networking, for networking with external professional contacts, and for internal networking within the company. Compared to 2008, the utility for external professional networking increased in 2011 (Archambault & Grudin, 2012).For internal networking, only half of the employees believe it is useful. A common source of skepticism towards internal networking use of social media was that people's social networks transcend company boundaries, limiting what can be said on work topics.

The study also examined age as a factor affecting social media use. The authors found that LinkedIn appeals more to professionals between 25 and 40 years of age, rather than young students. The study also revealed an issue that may inhibit user activity in social media: as the size and diversity of the network grew, posting items of interest to a small subset became less appealing. This creates an opportunity for specialized, differentiated tools and maybe a factor driving the success of LinkedIn.

Another three studies reviewed applied the use and gratifications (U&G) theoretical framework to explain why consumers use social media. According to the U&G theory, individuals actively seek to fulfill their needs through the use of media. This theory had been originally developed to analyze traditional media, but various studies have demonstrated that it can also be applied to social media.

The relevance of the U&G approach is that there is evidence that gratifications received are good predictors of media use and recurring media use (Whiting& Williams, 2013). Hence, understanding the types of gratifications received by consumers from social media could help businesses develop the appropriate strategies to increase the use of social media.

A study by Whiting and Williams identified ten uses and gratifications for using social media. The methodology consisted of 25 in-depth interviews with subjects of ages ranging from 18 to 56 years old. Subjects were asked questions such as why they use social media, why their friends use it, what they enjoy about it, and how often they use it. The gratifications identified were social interaction (99%), information seeking (80%), pass time (76%), entertainment (64%), relaxation (66%), convenience utility (52%), information sharing (40%), and surveillance and watching of others (20%).

Whiting and Williams demonstrated that the U&G theory can be applied to social media. One limitation of this study is the small sample size and the fact that it does not focus on any particular type of social media.

Quan-Haase and Young also applied the U & G approach to analyze social media, but their study aimed at demonstrating how different social media fulfill different user needs. They did a comparative study between Facebook and instant messaging. Employing surveys and interviews with undergraduate university students, the authors identified similarities and differences in gratifications received from the two different types of social media (Quan-Haase &Young, 2010).

Their findings revealed that both Facebook and IM have very similar uses and fulfill similar communication and socialization needs: they are both used as pastime activities to have fun, kill time, relax, and provide a form of escape from everyday responsibilities. However, they also identified small differences in the gratifications obtained. Even though these differences are small, they are sufficient to explain the different ways in which users employ these two forms of social media. Facebook is used to find out about social events, friends' activities, and social information about peers. Although these can also be achieved through IM, it is not as effective as Facebook for two main reasons: first, users have to communicate with each friend separately instead of broadcasting to their entire network as it is with Facebook; second, IM requires both users to be online simultaneously, whereas Facebook allows for asynchronous communication. Therefore, although both social media types provide social information to users, Facebook fulfills a unique need by allowing users to conveniently broadcast social information asynchronously (Quan-Haase & Young).

This study provides opportunities for future research by incorporating a wider range of items in the gratifications sought and obtained. Besides, future research could compare gratifications sought and received from Facebook with other social media.

Yet another study that utilized the U&G approach to analyze social media use was performed by Wang, Tchernev, and Solloway in 2010. This study differs from the other two in that it examined the dynamic relationship between social media use, needs and gratifications, and their self-sustaining feedback effects. By collecting samples of experience data from college students throughout four weeks, this study revealed that social media use is driven by four categories of needs, namely social, emotional, cognitive, and habitual, but only gratifies some of them. The ungratified needs accumulate over time and drive future social media use. Another finding was that interpersonal social environments also affect social media use.

The current literature shows that there have been studies focused on understanding what motivates social media use. However, the current literature does not specifically focus on LinkedIn. Therefore, this study will aim at understanding the relationship between consumers' needs, gratifications obtained, and demographic and behavioral factors affecting the use of LinkedIn.

III. Research Methods

An online survey was developed and distributed using the Survey Gizmo software to existing LinkedIn members in the United States. Respondents were surveyed from November 21 to December 12, 2016. Participation was voluntary and participants were provided (with) a consent form before beginning the survey.

IV. Research Sample

A total of 109 responses were collected, and this sample was reduced to 104 after incomplete responses were removed. The survey was used as a quantitative and qualitative research methodology. The following sections will describe each methodology in detail.

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V. Quantitative Methods

The quantitative methods consisted of survey questions with close-ended answers, such as Yes/No questions and Likert scale questions. An example of a quantitative question included in the survey was "How often do you login to LinkedIn?" where respondents were asked to respond using a 1-5 point Likert scale, as shown in *Figure 1*.

The quantitative questions allow one to generate numerical data to quantify the distribution of the sample's demographic data, attitudes, and behaviors towards LinkedIn.

Besides, the quantitative data allows one to perform statistical analysis, such as analysis of variance, to test the significance of the differences in login frequencies to LinkedIn identified for various groups in the sample. Furthermore, quantitative data allows one to perform correlation analysis between the independent variables (demographic and behavioral variables) and the dependent variable (login frequency to LinkedIn).

VI. Qualitative Methods

The survey was also used as a qualitative research methodology by including one open-ended question where participants were asked to provide their opinions and suggestions on improvements that would drive more frequent login to the LinkedIn platform.

The qualitative data were manually analyzed to identify trends in opinions that ultimately help to uncover elements that would encourage LinkedIn members to login to the platform more frequently.

The quantitative data allows one to describe a certain thing or phenomenon through the natural language of participants. Also, the quantitative data lets the voice of LinkedIn members be heard, allows one to understand the real users' feelings, ideas, and motivations behind their behaviors.

VII. Data Analyses

To assess the differences in login frequency among different demographic and behavioral characteristics, the mean and standard deviations of the login frequency were calculated for each group.

The mean represents the average login frequency within a group, and the standard deviation measures the amount of variation in the login frequency reported in a group.

To determine whether the mean login frequencies were significantly different among various groups, analysis of variance was performed. In each case, the p-value < 0.05 indicates there are statistically significant differences among the mean login frequencies. A p-value > 0.05 confirms that the mean login frequencies among various groups are equal.

a) Relationship between demographic characteristics and login frequency

Table 1: Age distribution and LinkedIn login frequency per age group

Age group	% of respondents	Mean Login Frequency	Standard Deviation
18-25	12%	3.461538	0.9674179
26-40	73%	3.763158	1.1415594
41-60	9%	3.888889	1.0540926
60+	6%	4.000000	1.2649111

Table 1 shows the sample's age distribution, and the mean and standard deviations of login frequency obtained for each age group. Most survey respondents belong to the 26-40 age group, which constitutes 73% of the total sample. The second-largest age group is 18-25 (12%), followed by 41-60 (9%) and 60+ (6%).

The results show that as the age group increases, so does the mean login frequency to LinkedIn. The 60+ age group has the highest mean login frequency but also the highest standard deviation.

To determine whether the differences in login frequency means are significant among the age groups, analysis of variance was performed. Because the sample data did not satisfy the assumptions of normality of residuals, the Kruskal-Wallis non-parametric test was performed. The test indicated that there are no significant differences in login frequency among the different age groups ($\chi^2(3) = 1.8161$, p-value $= 0.6114$).

Table 2: Gender distribution and LinkedIn login frequency per gender group

Gender	% of respondents	Mean Login Frequency	Standard Deviation
Female	58%	3.666667	1.084039
Male	42%	3.863636	1.153174

Table 2 shows the sample's gender distribution, and the mean and standard deviations of login frequency obtained for each gender group.

The distribution of female and male respondents was fairly even, with 58% female and 42% male respondents.

Male respondents reported a higher mean login frequency and a higher standard deviation than female respondents. To determine whether the difference in mean login frequency is significant, the Mann-Whitney-Wilcoxon non-parametric test was performed. The result indicated that there is no significant difference in mean login frequency between male and female respondents (W = 1166, p-value = 0.293).

Table 3: Distribution of education levels and LinkedIn login frequency per education level

Education level	% of respondents	Mean Login Frequency	Standard Deviation
High school diploma	3%	3.333333	1.154701
Bachelor's degree	21%	3.818182	1.097025
Postgraduate	73%	3.776316	1.138405
Other	3%	3.000000	0.000000

Table 3 shows the sample's distribution of education levels, and the mean and standard deviations of login frequency obtained for each education level.

The majority of respondents has postgraduate education level (73%), followed by a Bachelor's degree (21%). Only 3% of respondents reported "High school diploma", and another 3% reported "Other" type of education.

Respondents who reported a "Bachelor's degree" or "Postgraduate level" of education had the highest mean login frequency. Respondents who reported "Other" had the lowest login frequency and showed no variations in their login frequencies.

To determine whether the mean login frequencies are significantly different among the sample of different education levels, the Kruskal-Wallis non-parametric test was performed. The test indicated that there are no significant differences in login frequency among the different education levels ($\chi^2(3)=2.6513$, p-value = 0.4486).

Table 4: Distribution of occupation and login frequency per occupation

Occupation	% of respondents	Mean login frequency	Standard deviation
Engineering	26%	3.703704	1.0675210
Business and financial	18%	4.052632	1.0259784
Management	18%	3.684211	1.1572300
Computer science	8%	3.875000	1.3562027
Other	7%	4.142857	0.6900656
Healthcare practitioner	6%	2.833333	1.3291601
Fresh graduate	5%	3.800000	1.0954451
Research	4%	3.500000	1.2909944
Education	3%	3.333333	1.5275252
Media and communications	3%	3.666667	1.5275252
Art and design	1%	4.000000	-
Law	1%	3.000000	-
Sales	1%	5.000000	-

Table 4 shows the sample's distribution of occupations, and the mean and standard deviations of login frequency obtained for each occupation group.

Most survey respondents belong to the Engineering occupation (26%), followed by Business and financial (16%), and Management (16%). These three groups of occupations represent 66% of the sample.

The results show that the Sales category has the highest mean login frequency (M=5.00) and the standard deviation is not reported due to only one respondent belonging to this category. Respondents who reported occupation as "Other" had the second-highest mean login frequency (M=4.14), followed by business and financial (M=4.05).

To determine whether the mean login frequencies are significantly different among occupation groups, the Kruskal-Wallis non-parametric test was performed. The result indicated that there are no significant differences in login frequency among the different education levels ($\chi^2(12)$ = 8.3805, p-value = 0.7547).

Table 5: Distribution of access channels and LinkedIn login frequency per access channel

Access channel	% of respondents	Mean Login Frequency	Standard Deviation
Computer	33%	3.200000	1.207818
Mobile app	8%	3.250000	1.164965
Computer and mobile app	59%	4.131148	0.884598

Table 5 shows the sample's distribution of LinkedIn access channels, and the mean and standard deviations of login frequency obtained for each group.

The majority of respondents reported accessing LinkedIn from both computer and mobile app channels (59%), 33% only access it from the computer, and only 8% access it from the mobile app.

To determine whether the mean login frequencies are significantly different respondents using different access channels, the Kruskal-Wallis non-parametric test was performed. The test indicated that at least two groups have significantly different login frequencies ($\chi^2(2)$ =15.4831, p-value = 0.0004344).

To identify the groups that are significantly different, the Nemenyi-test for multiple comparisons was performed as a post-hoc test. The results are shown in Table 6.

The post-hoc test results return the lower triangle of a matrix containing the p-values of the pair wise comparisons. A p-value lower than 0.05 indicates that a pair of categories have significantly different mean login frequencies. the lower the p-value, the stronger the evidence that there are significant differences in mean login frequencies between the pair of categories. A p-value equal to or higher than 0.05 indicates that a pair of categories have the same mean login frequencies. The larger the p-value, the stronger the evidence that the pair of categories have the same mean login frequencies.

Table 6: Results of Nemenyi multiple comparisons test

	Computer and mobile app	Computer
Computer	0.0011	
Mobile app	0.1174	0.9996

As per the results in Table 6, the "Computer" and "Computer and mobile app" have significantly different mean motivation scores (p-value = 0.0011). That means that respondents who use both computer and mobile applications to access LinkedIn, login more frequently than respondents who only use the computer.

There is strong evidence that the means in login frequency among the "Computer" and "Mobile app" groups are the same (p-value = -.9996). There is also evidence, though weaker, that the mean login frequencies between "Mobile app" and "Computer and mobile app" are the same.

Table 7: Distribution of respondents who are seeking job or career advancement and those who are not. LinkedIn login frequency for both groups.

Seeking career development	% of respondents	Mean Login Frequency	Standard Deviation
Yes	51%	3.943396	1.026853
No	49%	3.54902	1.171558

Table 7 shows the sample's distribution of respondents who reported they are looking for jobs or career advancements and those who do not. Means and standard deviations for each group are also reported.

There was an even distribution of respondents who were looking for jobs or to advance in their careers, and those who were not. The respondents who reported seeking jobs or career advancement displayed a higher mean login frequency (3.94) than those who are not seeking jobs or career advancement.

The Mann-Whitney-Wilcoxon non-parametric test was performed to test the significance of the mean differences. The test indicated that there are no significant differences in login frequency among both groups (W = 1098.5, p-value = 0.08735).

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Table 8: Distribution of job satisfaction levels and LinkedIn login frequency per job satisfaction

Job satisfaction	% of respondents	Mean Login Frequency	Standard Deviation
Very dissatisfied	1%	5	-
Dissatisfied	4%	4.25	1.5
Neutral	29%	3.766667	0.971431
Satisfied	48%	3.72	1.178723
Very satisfied	18%	3.631579	1.116071

Table 8 shows the sample's distribution of job satisfaction levels, and the mean and standard deviations of login frequency obtained for each group.

Almost half of the respondents reported, "Satisfied". By combining "Satisfied" and "Very Satisfied", 66% of respondents are satisfied with their current jobs. 29% were neutral about their current jobs and by combining "Dissatisfied" and "Very Dissatisfied", a total of 5% reported dissatisfaction with their current jobs.

Only one respondent felt "Very dissatisfied" about the current job and reported the highest mean login frequency (M=5.00). The "Dissatisfied" group has the second-highest mean login frequency (M=4.25) but also the highest variation of login frequencies reported (SD = 1.5) groups. The "Neutral", "Satisfied", and "Very Satisfied" groups had lower mean login frequencies.

A Kruskal-Wallis test was performed to test the significance of the mean differences. The result showed no significant differences in mean login frequency among the groups ($\chi^2(4)$ =3.1479, p-value = 0.5334).

Table 9: Distribution of involvement in professional organizations and LinkedIn login frequency per each group

Involvement in professional organizations	% of respondents	Mean Login Frequency	Standard Deviation
Yes	57%	3.79661	1.126172
No	43%	3.688889	1.10417

Table 9 shows the sample's distribution of respondents' involvement in professional organizations, and the mean and standard deviations of login frequency obtained for both groups.

The Mann-Whitney-Wilcoxon non-parametric test was performed, and the result indicated that there are no significant differences in login frequency among both groups (W = 1246, p-value = 0.58).

Table 10: Sample survey results collected from one respondent's motivations to use LinkedIn

Motivation category: I use LinkedIn for...	Rating *1: Strongly disagree; 2: Disagree; 3: Neutral; 4: Agree; 5: Strongly agree*
Networking	5
Socializing	2
Job search	5
News and events	3
Developing my portfolio	4
Research and publications	4
Business and product promotion	4
Learning	1

To assess the LinkedIn members' motivations to use the platform, survey participants were provided with statements regarding different reasons to use LinkedIn and asked to rate their level of agreement with these statements using a 1-5 point Likert scale (1: Strongly disagree; 5: Strongly agree).

An example of results collected for one respondent is shown in Table 10. The motivation rating reported for each category measures the extent to which that category encourages the use of the LinkedIn platform. For example, a rating of "5" for "Networking" and a rating of "2" for "Socializing", indicate that networking is a stronger motivation than socializing to use LinkedIn.

Table 11: Distribution of motivations to use LinkedIn

I use LinkedIn to…	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
Networking	3%	2%	14%	38%	43%
Socializing	21%	37%	26%	15%	1%
Job search	3%	5%	12%	34%	46%
News and events	10%	37%	31%	21%	1%
Development of portfolio	5%	19%	34%	32%	10%
Research and publications	16%	37%	32%	13%	2%
Business promotion	17%	37%	30%	12%	4%
Learning	11%	28%	30%	24%	7%

Table 11 shows the distribution of motivation ratings across all survey respondents for each motivation category. By combining "Agree" and "Strongly Agree", 81% of survey respondents agreed with "Networking" as a motivation to use LinkedIn. "Networking" is closely followed by "Jobsearch", with 80% of respondents reporting agreement. "Development of portfolio" received a combined 42% of "Agree" and "Strongly Agree" ratings. The combined "Agree" and "Strongly agree" percentages for all other factors as motivations to use LinkedIn were significantly lower, with "Research and Publication being the lowest with only 15%.

To determine the main motivation to use LinkedIn, the means and standard deviations of motivation ratings were calculated for each motivation category across all survey respondents.

Table 12: Means and standard deviations of motivation ratings per motivation category

Motivation category	Mean motivation rating	Standard deviation of motivation rating
Networking	4.239583	0.8428622
Job search	4.104167	0.8519843
Developing portfolio	3.208333	0.9505308
Learning	2.854167	1.0855914
News and events	2.656250	0.9041207
Research and publications	2.489583	0.9513956
Business promotion	2.458333	1.0043764
Socialize	2.375000	0.9867544

The results obtained are reported in Table 12 in descending order concerning the mean motivation ratings. "Networking" has the highest mean (M=4.24), followed by "Jobsearch" (M=4.10), indicating that on average they were rated highest among all respondents. The standard deviations were highest for "Learning" (SD= 1.08) and "Business promotion" (1.00), which indicates they had the highest variation in ratings among respondents.

To determine whether the differences in mean motivation ratings are significant across the various categories, a Kruskal-Wallis test was performed. The result indicated that at least two categories have significantly different mean motivation ratings ($\chi^2(7)$ = 254.8488, p-value < 2.2e-16).

Table 13: Results of the Nemenyi multiple comparisons test

	Business and product promotion	Job search	Learning	Networking	News and events	Development of portfolio	Research and publications
Job search	9.1e-14	-	-	-	-	-	-
Learning	0.25666	2.3e-10	-	-	-	-	-
Networking	7.2e-14	0.99702	1.4e-12	-	-	-	-
News and events	0.94911	1.2e-13	0.92207	6.3e-14	-	-	-
Development of portfolio	0.00021	6.0e-05	0.41197	1.5e-06	0.01913	-	-

Research and publications	1.00000	9.9e-14	0.29737	8.0e-14	0.96498	0.00029	-
Socializing	0.99987	5.8e-14	0.09448	7.6e-14	0.76954	2.6e-05	2.6e-05

To identify the categories that were significantly different, the Nemenyi-test for multiple comparisons was performed as a post-hoc test. The results are shown in Table 13.

The post-hoc test results return the lower triangle of a matrix containing the p-values of the pair wise comparisons. A p-value lower than 0.05 indicates that a pair of motivation categories have significantly different mean motivation ratings. The lower the p-value, the stronger the evidence that there are significant differences in mean login frequencies between the pair of categories. A p-value equal to or higher than 0.05 indicates that a pair of categories have the same mean login frequencies. The larger the p-value, the stronger the evidence that the pair of categories have the same mean login frequencies.

The results show that the p-value for pair-wise comparison between "Job search" and "Networking" is 0.99702. This means that "Jobsearch" and "Networking" have the same mean motivation ratings. However, the p-value for the pair-wise comparison between" Job Search" and "Development of portfolio" is $6x10^{-5}$, which is lower than 0.05. This means that these two categories have different mean motivation scores.

Given these results, "Networking" and "Jobsearch", having equal mean motivation ratings, are the motivation categories with the highest reported mean motivation ratings.

Table 14: Frequency of improvement categories reported by survey respondents

Improvement category	Frequency
Content relevance	21
Job search experience	19
Ease of use	12
More offerings	7
Interactivity	6
Connection and network relevance	4
Privacy	4
Less restrictions for non-premium members	4
Pricing	3
Events	3
Learning	2
Contact information	1

To obtain a measure of the respondents' overall motivation to use LinkedIn, the average motivation rating was calculated as the average of motivation ratings across all motivation categories:

$$\begin{aligned} Average\ Motivation\ Rating \\ = (Rating_{Networking} + Rating_{Socializing} + Rating_{Job\ search} \\ + Rating_{News\ and\ events} + Rating_{Business\ promotion} + Rating_{Research\ and\ publications} \\ Rating_{Learning} + Rating_{Development\ of\ portfolio})/8 \end{aligned}$$

A correlation analysis was performed between the respondents' average motivation rating and login frequencies.

Because the data violated parametric assumptions, the Spearman rank coefficient obtained was calculated. A Spearman coefficient of 0. 3635777 (p- va lue=0.0001484) indicates a moderate positive correlation between average motivation rating and login frequency to LinkedIn.

b) *Suggested improvements to encourage higher login frequency to LinkedIn*

The respondents' suggestions on elements that would encourage higher frequency of login to LinkedIn were analyzed and grouped into 13 categories. Table 14 reports the frequency in which each category was reported by the survey respondents.

Content relevance and job search experience were the two most frequently mentioned elements that would encourage higher login frequency to LinkedIn.

Content relevance was reported 21 times. Various respondents claimed that they rarely find any interesting content on LinkedIn. Furthermore, they noted that LinkedIn was often used as a social platform instead of a strictly professional platform, making the content less relevant for professional purposes. Also, several respondents reported excessive advertising and spam in the LinkedIn platform, which further lowers the quality of the content.

The job search experience was reported 19 times. Respondents suggested that LinkedIn should enhance this experience by making it easier for job seekers to find relevant jobs, apply to those jobs, and facilitate networking with recruiters.

The third most frequently reported category relates to ease of use for both desktop and mobile LinkedIn platforms. These respondents reported that the platform is currently not user-friendly. The remaining categories of improvement were reported at a lower frequency.

VIII. Findings

a) *Relationship between demographic characteristics and login frequency*

There is no evidence to suggest that members of varying age, gender, education level, or occupation exhibit significant differences in their frequency of login to LinkedIn. This disproves the first hypothesis.

b) *Relationship between LinkedIn access channel and login frequency*

The data suggest that LinkedIn users who use both computer and mobile application channels to access LinkedIn log in more frequently than those who use only the computer or the mobile application. The second hypothesis is therefore valid.

c) *Relationship between attitudes towards career development and login frequency*

There is no strong evidence to suggest that members who are seeking career development log in more frequently to LinkedIn. There is no evidence to prove that members who are currently dissatisfied with their jobs or involved in professional organizations, exhibit higher login frequencies. The third hypothesis is therefore false.

d) *Main motivations to use LinkedIn*

The data suggest that the main motivations for using LinkedIn are job search and networking. It is worth noting that these two categories are not independent variables. Networking and job search are closely associated. Therefore, the fourth hypothesis is proved to be valid.

e) *Relationship between motivations to use LinkedIn and login frequency*

The correlation analysis showed that the higher the overall motivation to use LinkedIn, the higher the login frequency to LinkedIn. As the analysis suggests, there is a positive but weak correlation between these two variables. The fifth hypothesis is therefore proved to be valid.

f) *Suggested elements of improvement to encourage higher login frequency*

The data showed evidence that LinkedIn users would like improvements in diverse aspects of the platform. The two most popular aspects of improvement were "Content relevance" and "Job search experience".

Given that one of the major purposes of social media is to contribute, consume, and share interesting content with other users, it is not surprising that content relevance was the most frequently mentioned element for improvement to encourage higher login frequency to the LinkedIn platform.

Job search experience was the second most popular element for improvement. This is not surprising given that, as the previous analysis suggested, the job search is the members' main motivation to use LinkedIn. Therefore, it makes sense that members have identified pain points and areas of improvement that would encourage them to use the platform more frequently.

The third most popular element for improvement was the ease of use. This suggests that this is an important factor for LinkedIn users, and if it were enhanced, it could drive more frequent use of the platform.

IX. Recommendations

Based on the findings discussed, the following recommendations were developed:

- To increase members' frequency of login to the platform, LinkedIn should encourage members to be active in both channels: computer and mobile application. This could be done, for example, by encouraging mobile app downloads to members who currently do not use the mobile channel, and by improving the user experience in both computer and mobile channels.

- LinkedIn should focus on improving the user experience for two key areas: Networking and job search. Not only they are the two main motivations for members to login to the platform, but job search experience has also been identified as one of the critical elements that members would like to see improved to encourage higher login frequency. Although LinkedIn is the leading platform for networking in the US, it is not the leading platform for job searching yet. But by providing an exceptional job search experience, LinkedIn could become the leading platform for job searching as well. Doing so will result in higher member activity.
- LinkedIn should invest efforts to provide relevant content to its members. This was identified as one of the members' priority areas of improvement. LinkedIn should restrict excessive advertising and spam, and develop the tools to feed interesting and relevant content to its users. Doing so will encourage higher login frequency.
- LinkedIn should focus on raising awareness and encouraging the use of their offerings other than networking and job search, such as learning, business promotion, and searching for news and events. When members can identify with more motivations to use LinkedIn, they will login more frequently to the platform.

X. Limitations

One of the limitations of this study is the size of the sample. Due to time constraints, the sample size was limited to 104, which poses challenges to obtaining statistically significant results.

Besides, the sample is biased. The majority of survey respondents consisted of subjects within the researcher's social and professional circle. The majority of subjects belong to the 26-40 age group and have a postgraduate level of education. It was not possible to obtain a sample that is evenly distributed for age, education level, and occupation.

Furthermore, although the motivation categories presented in Table 12 are not independent, we assumed independence for the Nemenyi test conducted for multiple comparisons.

XI. Conclusion

This study demonstrated that LinkedIn user behavior can be assessed using a survey as a quantitative and qualitative methodology. This paper contributes to the existing literature by being the first study to ever examine LinkedIn user behavior. Also, this paper contributes valuable insights about users' motivations to use the platform and factors affecting login frequency that can help LinkedIn to develop strategies that will increase its monthly active users and increase its opportunities for revenue growth.

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