Open Source Software: A Detailed Analysis of Contributions and Quality

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Abstract

Open source software has been an option for many applications since the dawn of computing. Simply put, open source is "software for which the original source code is made freely available and may be redistributed and modified." (Oxford dictionary). But with this free software, there often comes little support and sometimes perceived or actual questionable quality. Our study examines the current attitudes and participation among the developer community towards contributing to open source software as well as the present perceptions of quality among this group. Overall, we find that levels of participation are relatively low but do vary by demographic factors. Also, the perceived levels of quality remain below proprietary/closed source software, but again, demographics and country of origin show much variation.

Keywords: Open source software, quality, contribution, adoption

1. INTRODUCTION

Open source software (OSS) is defined by Oxford dictionary (2020) as "software for which the original source code is made freely available and may be redistributed and modified." Some people may prefer using open source software over proprietary software for multiple reasons, including control, training, security, stability, and community. Developers have more control with OSS because they can examine the code and make changes as desired. Since open source code is publicly accessible, people can study it to become better programmers. Some users perceive OSS to be more secure than proprietary software since updates and fixes can be done without asking permission. OSS may be considered more stable since it can still be updated even if the original developers cease working on the software. In addition. OSS often creates a strong community of users and developers (https://opensource.com/).

Many people use some type of open source software on a daily basis. Table 1 displays examples of some of the most popular open software that has been released.

Wordpress	Magento
Mozilla Firefox	Mozilla Thunderbird
FileZilla	GnuCash
Audacity	GIMP
OpenOffice	VLC
Handbrake	Pidgin
Freemind	Notepad++
7-Zip	Blender
PDFCreator	Calibre
TrueCrypt	Ubuntu

Table 1: Popular OSS Examples

The rest of our paper is arranged as follows: the Literature Review examines previous research in this area, including the usage of several theories including the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT). Section 3 explains the methodology we used for this paper. Section 4 presents our results, while Section 5 provides discussion of these results along with conclusions.

2. LITERATURE REVIEW

A number of previous studies have examined the adoption of OSS. Some of these have used well-known theories such as the Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), along with additional constructs and theories, in order to better understand the factors influencing OSS adoption. Others have applied Grounded Theory, systemic literature reviews, frameworks, or other approaches.

Multiple researchers have used variations of TAM in their research regarding OSS adoption. Gallego et al. (2015) developed a research model based upon the Technology Acceptance Model, adding several constructs. The authors discovered that user training, user fit, technological complexity and trainers' support influence the adoption of OSS. Gwebu and Wang (2010) conducted an exploratory study of free open source software (FOSS) users' perceptions, using the Technology Acceptance Model along with other constructs. They identified potential barriers to FOSS adoption and provided recommendations that may increase adoption of FOSS. Gallego et al. (2007) identified the variables and factors that have a direct effect on individual attitude towards OSS adoption by using a variation of the technology acceptance model. Taha et al. (2018) examined the main factors affecting the adoption of OSS in the desktop environment. They administered over 340 questionnaires and found that quality, compatibility, support, and usability are the key factors that influence OSS adoption. Racero et al. (2020) examined students' behavioral intention to use OSS by combining the Technology Acceptance Model and Self-Determination Theory. They used the following constructs: Autonomy, competence, relatedness, perceived ease of use, perceived usefulness and behavioral intention. The results confirmed the positive influence of intrinsic motivations, autonomy and relatedness on the usefulness and ease of use and on behavioral intention to use Open Source Software.

Alrawashdeh et al. (2019) used an integrated model of OSS characteristics and UTAUT to survey 255 individuals working at public and private organizations. Software security, software interoperability, and software quality had a significant impact on performance expectancy. The authors concluded that effort expectancy, performance expectancy, self-efficacy, social influence, software cost, software interoperability, software quality, and software security are all important indicators in OSS acceptance and implementation.

Hauge, Ayala, and Conradi (2010) performed a systematic literature review of the adoption of open source software in software-intensive organizations. They identified 112 papers that provide empirical evidence on how organizations adopt OSS and created a classification framework consisting of six ways in which these organizations adopt OSS. The researchers found that existing research on OSS adoption does not sufficiently describe the context of the companies that are studied. Steinmacher et al. (2015) conducted a systematic literature review on the barriers faced by newcomers to open source software projects. They examined 291 studies using Grounded Theory to categorize the barriers into five groups: Social interaction, newcomers' previous knowledge, finding a way to start, documentation, and technical hurdles. They also classified the problems with regard to their origin into three categories: newcomers, community, or product. In order to examine OSS adoption in commercial firms, Thanasopon (2015) developed a framework consisting of four elements: external environment, organizational, technological, and individual contexts. The author found 14 factors that impact OSS adoption which fits into these four elements. Some of these factors encourage the adoption of OSS, while others are inhibitors.

Gwebu and Wang (2011) looked at the role of social identification in the adoption of OSS. The authors noted that most previous work had focused on OSS adoption at the organizational level; minimal work existed at the individual level. They found that social identification is a key driver of OSS adoption. Marsan, Pare, and Beaudry (2012) applied the socio-cognitive perspective of IT innovation adoption and the organizing vision theory by surveying 271 IT specialists in order to better understand the adoption of OSS in organizations. They classified specialists into two groups: Detractors and supporters. Detractors possess more years of experience but have less exposure to OSS than supporters. The perceptions of IT specialists are positively associated with their company's openness to OSS adoption and the existence of an organizational policy that favors the adoption of OSS.

Katsamakas and Xin (2019) created a game-theoretic analytical model to explain when organizations adopt open source software applications and platforms and to explore the implications. Their analysis examines whether adoption patterns are socially beneficial. They found that open-source adoption depends upon organizational IT capabilities, network effects, and the fit of OSS with the company's application needs. Their results imply that open-source adoption can be socially inefficient.

Lopez et al. (2015) modeled OSS adoption strategies using a goal-oriented notation, examining objectives and dependencies to explore the consequences of adopting one strategy vs. another. They applied their approach to a large telecommunications company.

Sarrab and Rehman (2014) noted that governments and organizations are beginning to adopt OSS on a large scale. They conducted an empirical study of OSS adoption based upon software quality characteristics. Their research used additional internal quality characteristics for selecting OSS that were added to the dimensions of DeLone and McLean information systems' model. The authors organized the quality characteristics into a hierarchy, in which they list characteristics with three main dimensions of quality: information, service, and system.

Sbaia et al. (2018) mentioned that OSS is being adopted more by both organizations and individuals. They examined multiple OSS adoption models and used a case study approach to determine what information can be automatically retrieved from OSS platforms such as GitHub, SonarCloud, and StackExchange.

Silic and Back (2015) examined the influence of risk factors in the decision-making process for OSS adoption. They surveyed 188 IT decision-makers using an Open Source Risk Adoption Model to look at the perceived IT security risk relationship with the intention to adopt OSS. The authors found that IT security risk significantly influences OSS adoption intention.

Donga et al. (2019) suggest that innovation speed of OSS projects can influence users' interest in downloading and using the software. They used a large-scale panel data set from 7442 OSS projects on SourceForge between 2007 and 2010 and found inverted U-shaped relationships between initial release speed and user downloads, as well as between user downloads and update speed.

Most previous research has used much smaller data sets than what we use in our study.

3. METHODOLOGY

In order to study the current usage of open source software, we used the comprehensive 2019 Stack Overflow survey with over 88,000 respondents. Stack Overflow's annual Developer Survey is the largest and most comprehensive survey of people who code around the world. Each year, they field a survey covering everything from developers' favorite technologies to their job preferences. This year (2019) marked the ninth year they've published their annual Developer Survey results, and nearly 90,000 developers took the 20-minute survey earlier this year. (Stack Overflow, 2019). Despite our survey's broad reach and capacity in forming valuable conclusions, we acknowledge that our results don't represent everyone in the software community evenly. But, the 2019 survey had nearly 90,000 respondents and nearly 70,000 of those respondents were employed as software professionals. Our results include selected questions from the survey as well as detailed demographics available. The results were analyzed using IBM SPSS 26.

Our main research questions are focused on two areas participation and perceived quality:

RQ1 How active is the developer community in open source projects?
RQ1a Are there demographic and geographic differences in the developer community in participation in open source projects?
RQ2 What is the perceived quality of open source projects?
RQ2a Are there demographic and geographic differences in the developer community in perceived quality of open source projects?

4. RESULTS

Two specific questions in the survey asked whether respondents contributed to open source projects and also their opinion of the quality of open source software relative to proprietary or closed source software, basically commercial software:

How often do you contribute to open source?

1. Never
2. Less than once per year

3. Less than once a month but more than once per year
4. Once a month or more often;

and

How do you feel about the quality of open source software (OSS)?

1. OSS is, on average, of HIGHER quality than proprietary / closed source software
2. The quality of OSS and closed source software is about the same
3. OSS is, on average, of LOWER quality than proprietary / closed source software

Table 2 shows the overall means for these two questions based on the 86000+ responses. Overall, participation is slightly better than once a year. But this measure of central tendency is a bit misleading. The largest percentage of respondents did not contribute to open source software as shown in Table 3. Over 36% have NEVER contributed to open source. Overall, though this means that 64% have contributed at some time. 64% have either never or less than once per year but also 64% did at some point. We

		Freq.	Percent	Valid Percent	Cum. Percent
Valid	Higher Quality	8759	9.9	10.1	10.1
	Same	41527	46.7	47.8	57.9
	Lower Quality	36556	41.1	42.1	100.0
	Total	86842	97.7	100.0	
Miss.	System	2042	2.3		
Total		88884	100.0		

believe this shows an active participation among the developer community in open source projects. We must note of course that participation in this survey serves as somewhat of a bias and may not represent the entire developer population but we do believe that this result does indicate an active and significant force in the software field.

		OPEN SOURCE PARTICIPATION	OPEN SOURCE QUALITY
N	Valid	88883	86842
	Missing	1	2042
Mean		2.11674	2.32009

Table 2: Means for Open Source Participation and Quality

		Freq.	Percent	Valid Percent	Cum. Percent
Valid	Never	32295	36.3	36.3	36.3
	Less than Once per year	24972	28.1	28.1	64.4
	1 mon– 1 year	20561	23.1	23.1	87.6
	More 1 per mon.	11055	12.4	12.4	100.0
	Total	88883	100.0	100.0	
Miss.	System	1	.0		
Total		88884	100.0		

Table 3: Open Source Participation

As noted, many researchers have suggested that open source software may be viewed by the population as of lesser quality than proprietary/closed/commercial software. The mean pf 2.32 suggests a perceived somewhat lower quality since 2 is equal and 3 is lesser. Quality of Open source software was seen by 42% as lower quality (Table 5) but 47% saw as same quality as Proprietary software. Only 11% saw as better. The fact that 47% saw open source software was seen as equal quality suggests that not all view open source software poorly. In fact, nearly half see as equal.

(I)1=Male,2=Female, 3=Other	(J)1=Male,2=Female, 3=Other	Sig.
1	2	.000
	3	.001
2	1	.000
	3	.000
3	1	.001
	2	.000

Table 4: Post Hoc Analysis
Table 5: Quality Analysis

The other area of our research questions was to explore whether there were demographic and/or geographic differences in participation and perceived quality. Variables available to us in the survey and used to explore for significant differences were Age, Gender, Years programming, Year started programming, Race, Professionals versus non-professionals, and Country. We examined all these variables.

1=Male, 2=Female, 3=Other	Mean	N	Std. Deviation
1	2.13563	77919	1.034646
2	1.82282	6344	.996989
3	2.19306	4439	1.097084

Total	2.11613	88702	1.038480

Table 6: Age and Gender ($p < .001$)

The first variable analyzed was gender. There were 8 categories of gender which we compressed to 3 categories because of low numbers in the neither male nor female identities. The results are in Table 6. Overall males were significantly more likely to participate in open source projects than females. This may suggest a gender bias in contributing to open source groups. There was no such difference with other gender participants. In fact, other gender were significantly higher than either male or female as shown in the Table 4. All variances were significant at $p < .01$.

OPEN SOURCE PARTICIPATION

Age Group	Mean	N	Std. Deviation
5-30	2.09011	47544	1.046185
31-50	2.16646	28722	1.013663
51+	1.98947	2943	.995003
Total	2.11405	79209	1.033548

Table 7: Age Group Analysis

Table 7 shows the open source participation by age group. The highest participation is by the 31-50 age group, followed by the 5-30. (Yes, there was a self-identified respondent age 5). It appears that older, more mature individuals in mid-career or age appear to have skills, time, and/or desire to participate in open source. For all these groups an ANOVA and Post hoc showed $p < .001$.

A between-subjects F test was performed with open source participation as the dependent variable and age group and gender as independent variables. The test showed no interaction effect for the two variables. (Table 8 in Appendix A)

Another research question examined was whether there were demographic differences with regard to perceived quality of open source software relative to closed source. Table 9 shows the results of perceived open source quality by gender. Surprisingly, there are no significant difference in quality based on gender.

Report

OPEN SOURCE QUALITY

1=Male, 2=Female, 3=Other	Mean	N	Std. Deviation
1	2.32075	76422	.647843
2	2.31184	6064	.619027
3	2.31682	4179	.683969
Total	2.31993	86665	.647659

Table 9: Perceived Quality by Gender

Differences based on age group however do exist. The youngest group rates open source significantly more unfavorably than the 31-50 and in turn the 31-50 rate open source significantly more unfavorable than the 51+. The older you are the higher you rate open source quality. The reason for this is unclear. Perhaps older users have had more and longer term exposure to open source. A Between-subject F test showed no interaction effects between age group and gender for this variable.

OPEN SOURCE QUALITY

Age Group	Mean	N	Std. Deviation
5-30	2.33444	46483	.657144
31-50	2.30763	28294	.621326
51+	2.25552	2853	.620683
Total	2.32177	77630	.643239

Table 10: Comparison of Age Groups ($p < .001$)

Within our dataset, there were questions about how many years the respondent has been coding and at what age they started. We anticipated that the more years coding and the younger individuals started coding, the more likely they were to contribute to open source projects and the more years coding more likely to view open source favorably. Tables 11 and 12 analyze these two independent variables. Open source participation was significantly positively correlated with years coding. The more years coding the higher the participation rate. And the more years coding, the more favorably open source is viewed (reverse scaled). When we examine age first coded however, we see slightly different results. The earlier a respondent started coding, the lower the quality perception. These apparently contradictory measures suggest the more you code but the older you start, the higher the participation and more favorable the perception. This suggests that perhaps open source is undervalued by the younger starters since they may be excluded from exposure at an early age.

Coefficients

Model		Unstd. Coefficients B	Std. Error	Std. Coefficients Beta	t	Sig.
1	(Con.)	2.411	.014		172.633	.000
	Years Code	.007	.000	.061	17.504	.000
	Age 1st Code	-.024	.001	-.115	-32.648	.000

a. Dependent Variable: OPEN SOURCE PARTICIPATION

Table 11

Coefficients

Model		Unstd. Coefficients B	Std. Error	Std. Coefficients Beta	t	Sig.
1	(Con.)	2.370	.009		264.961	.000
	Years Code	-.002	.000	-.028	-7.946	.000
	Age 1st Code	-.002	.000	-.012	-3.395	.001

a. Dependent Variable: OPEN SOURCE QUALITY

Table 12

*. The mean difference is significant at the .05 level.

Professionals are statistically more likely to participate in open source projects but also view open source as of lesser quality. This quality difference could be related to the exposure professionals receive with closed source projects and company's implementing more closed source solutions. Non-professionals often have to utilize more open source products due to cost concerns.

OPEN SOURCE PARTICIPATION

DEV	Mean	N	Std. Deviation
No	2.03288	23204	1.072591
Yes	2.14636	65679	1.024607
Total	2.11674	88883	1.038538

$p < .001$

Table 13

OPEN SOURCE QUALITY

DEV	Mean	N	Std. Deviation
No	2.29953	22342	.665600
Yes	2.32721	64500	.641071
Total	2.32009	86842	.647579

$p < .001$

Table 14

The final area we examined was geographical differences. We excluded countries where there were less than 500 respondents to ensure we had a critical mass. The results are shown in Tables 15 and 16. The highest contributions came from some interesting sources with Iran, China, and Bangladesh at the top of the list. This was followed by several European countries, Switzerland, Germany, and the Netherlands. The United States is ranked number 22 in this list of participation rates.

Country	Mean	N	Std. Deviation
Iran	2.43902	738	1.029916
China	2.42018	664	1.044825
Bangladesh	2.31901	605	1.144691
Switzerland	2.29857	978	1.072985
Germany	2.25281	5866	1.027340
Netherlands	2.24298	1852	1.027619
Czech Republic	2.21728	764	1.076334
Austria	2.21216	839	1.054729
India	2.21046	9061	1.106954
Norway	2.17944	574	1.008271
Nigeria	2.16667	522	1.139502
Denmark	2.16370	617	1.026015
France	2.16060	2391	1.051066
Turkey	2.16017	949	1.016558
Australia	2.15554	1903	1.024915
Israel	2.15336	952	1.021128
Finland	2.14652	546	1.024720
Pakistan	2.12134	923	1.093468
Belgium	2.11692	727	1.030567
Sweden	2.09733	1274	0.998007
United States	2.09351	20949	1.024844
Russian Federation	2.08619	1694	1.021163
Hungary	2.08187	513	1.016045
New Zealand	2.08015	524	1.024213
United Kingdom	2.06240	5737	1.032733
Italy	2.06028	1576	0.996907
Spain	2.05611	1604	0.985532
Canada	2.03594	3395	1.008160
Brazil	2.03388	1948	0.972071

Greece	2.02878	556	1.000486
Ukraine	2.01843	868	0.999253
Bulgaria	2.01821	659	0.973651
Poland	2.01457	1922	1.020761
Argentina	1.99458	553	0.978930
Portugal	1.99429	525	0.981686
Ireland	1.97804	501	0.994745
Romania	1.96579	760	0.989477
Indonesia	1.95464	507	1.009791
South Africa	1.94896	627	0.984194
Mexico	1.85981	642	0.927465

Table 15: Highest contributions by country

Belief in the quality of open source by country reveals a much different list. The Russian federation has the highest regard for open source versus closed source software, followed by Ukraine, New Zealand, Poland, Bulgaria. With the exception of New Zealand, these are all former Soviet bloc countries and may reflect their limited resources or lesser trust in "Western" sources.

Country	Mean	N	Std. Deviation
Russian Federation	2.13983	1652	0.641158
Ukraine	2.17882	850	0.664442
New Zealand	2.25832	511	0.641539
Poland	2.26223	1880	0.654016
Bulgaria	2.27315	648	0.679409
South Africa	2.27406	613	0.666615
Mexico	2.27473	637	0.645404
Canada	2.28468	3330	0.619625
Pakistan	2.29385	895	0.746143
Romania	2.29690	741	0.650034
Portugal	2.29709	515	0.619944
Israel	2.29803	916	0.650881
Turkey	2.30270	925	0.714145
Czech Republic	2.30470	745	0.619826
United Kingdom	2.31502	5625	0.619127
Finland	2.31648	534	0.602551
United States	2.31850	20543	0.615852
China	2.32258	651	0.727755
Austria	2.32278	821	0.626122
Iran	2.32489	711	0.735373
Greece	2.32532	541	0.678701
Italy	2.32751	1545	0.643964
Sweden	2.33008	1230	0.617079
Australia	2.33030	1871	0.625600
Switzerland	2.33090	958	0.604844
Belgium	2.33616	708	0.594642
Germany	2.34642	5756	0.609972
Denmark	2.35585	607	0.614909
Bangladesh	2.35986	578	0.762133
Brazil	2.36137	1926	0.657617
Norway	2.36348	564	0.628635
Netherlands	2.36900	1813	0.598996
Nigeria	2.37126	501	0.699923
India	2.38019	8772	0.715249
France	2.39966	2342	0.608188
Spain	2.40280	1569	0.604737
Argentina	2.43203	537	0.622599

Table 16

5. DISCUSSION AND CONCLUSIONS

The study of the use, acceptance, and adoption of open source software has mainly focused on limited datasets. Though our study has limited specificity on reasons for adoption, it is the first comprehensive review on practitioner attitudes and quality perceptions of open source software. In this way, it extends and supports some of the conclusions of prior research. Past research on open source software has focused on relatively small datasets or limited sample population.

Our study found that overall quality perception for open source software is significantly less than closed source. Gallego et al. (2015) and Taha et al. (2018) suggest training and support are key variables in acceptance of OSS. The lack of support inherent in open source may be a key factor in its perceived quality shortfall.

Racero et al. (2020) suggested that intrinsic motivation plays a key role intention to use OSS. Positive exposure to the software may be a path to a higher perceived quality.

Hagu, Ayala, and Conradi did not find clear reasons for lack of OSS adoption. The lack of received quality we found appears to be a fundamental reason.

Participation in OSS was studied by Gwebu and Wang and they found social identification as a key driver of adoption. This social aspect may be missing in many OSS projects and can be addressed.

One of the key influencers of OSS perception is security risk according to Silic and Back (2015). This may be a key underlying factor in our discovered quality shortfall.

There is much to be gained by use of open source software. Cost savings, transparent logic, and worldwide community input all serve as motivators to implement OSS solutions. Many developers are already engaged in contributing to OSS projects. But the numbers are not as robust as they could be. Further research is needed to more fully understand why OSS is not viewed as favorably as closed source software and practices and platforms need to be further refined so that more individuals can contribute to OSS. Wikipedia and its open source knowledge base has replaced many sources of general information. The potential exists for OSS to do likewise for business and personal software.

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Appendices and Annexures

Appendix A
Tests of Between-Subjects Effects
Dependent Variable: OPEN SOURCE PARTICIPATION

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
Intercept	Hypothesis	16320.922	1	16320.922	321.623	.003
	Error	102.699	2.024	50.745[a]		
Age Group	Hypothesis	29.394	2	14.697	23.570	.000
	Error	25.682	41.187	.624[b]		
Gender	Hypothesis	140.635	2	70.317	89.992	.000
	Error	124.202	158.954	.781[c]		
Age Group * Gender	Hypothesis	1.307	4	.327	.309	.872
	Error	83693.914	79036	1.059[d]		

a. .717 MS(GEN2) + .283 MS(Error)
b. .595 MS(AgeGroup * GEN2) + .405 MS(Error)
c. .379 MS(AgeGroup * GEN2) + .621 MS(Error)
d. MS(Error)
Table 7