Deconstructing Agile Survey to Identify Agile Skeptics

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Abstract

In empirical software engineering research, there is an increased use of questionnaires and surveys to collect information from practitioners. Typically, such data is then analyzed based on overall, descriptive statistics. Overall, they consider the whole survey population as a single group with some sampling techniques to extract varieties. In some cases, the population is also partitioned into sub-groups based on some background information. However, this does not reveal opinion diversity properly as similar opinions can exist in different segments of the population, whereas people within the same group might have different opinions. Even though existing approach can capture the general trends there is a risk that the opinions of different sub-groups are lost. The problem becomes more complex in case of longitudinal studies where minority opinions might fade or resolute over time. Survey based longitudinal data may have some potential patterns which can be extracted through a clustering process. It may reveal new information and attract attention to alternative perspectives. We suggest using a data mining approach to finding the diversity among the different groups in longitudinal studies (agile skeptics). In our study, we show that diversity can be revealed and tracked over time with the use of clustering approach, and the minorities have an opportunity to be heard.

Keywords:

Longitudinal Studies, Clustering, Opinion Diversity, Agile skeptics, Expert Opinion.

1. Introduction

Collecting survey data from software development practitioners to analyze statistically is one of the key areas of software engineering research[1]. Experts can have conflicting opinions and different experiences when using software and social media. Many different types of data are generated during the software development process. Some typical forms of data types [2]: Code bases, traces logs, historical code changes, fault databases etc. Large investments have recently been made in software process automation to reduce development costs while also improving quality. Automation processes gives a chance to storing and extraction new forms of data in addition of produces some traditional forms of data. Some of the other forms of software engineering data like : Test cases, System build traces, Team and personal data and Development process data [3]. In recent time online facilities and tools make it easier to collect survey opinions in a frequent manner, so a considerable amount of survey data is present in most of the software organizations.

We notice that most of the survey analyses are performed using traditional statistical methods and measures (like mean, median, variance and some data analysis tests) for their findings [4]. Overall, they consider the whole survey population as a single group with some sampling techniques to extract varieties [5]. In some cases, the population is also partitioned into subgroups based on some background information [4]. That does not reveal opinion diversity properly as similar opinions can exist in different segments of the population, whereas people within the same group might have different opinions. The problem becomes more complex in case of Longitudinal Study[1], where minority opinions might fade or resolute over time.

In this study, we applied clustering techniques on longitudinal opinion survey data which are collected in a categorical form. Clustering without any perceived bias divides the population into different clusters of sub-populations which to some degree have a similar opinion. There are some benefits and opportunities using this approach such as:

- It can reduce manipulation in grouping, as it generates groups based on their opinion.

[1] A Longitudinal study (LS) is an observational research method in which data is gathered for the same subjects frequently over a period. Longitudinal research projects can extend over years or even decades. Longitudinal study allows researchers to study changes over time through the individuals are observed over the study period. LS generate valuable empirical data. Moreover, longitudinal studies allow changes over time to be traced which means that the life of a system, process or practice can be better understood. It also means that the temporal aspects of process change can be observed. The scale and richness of data collected over a long period of time is a valuable empirical evidence which can be used to understand the study subject deeply [19].

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Furthermore, when clustering is used, basic information can also be integrated with opinions.

- It can exhibit opinion difference in the population more precisely. Statistical variance [4] can only show overall agreement or disagreement, whereas grouping by Data Mining (clustering) can show variance in each group and intra-group agreement and disagreement.
- It can identify minority groups which would not be identified otherwise. In most cases, minority groups lose their voices as results are presented in a more aggregated manner. In a longitudinal study a consistent alternative opinion over years may suggest some degree of strong conviction.
- Opinion difference and background information may reveal groups with distinct characteristics which may lead to generating valid hypotheses. In consequence more studies can be designed to investigate those groups and related hypotheses.
- In some cases, certain forms of correlation between different aspects of opinion are only visible within a cluster and are not obvious until cluster formation.

We used three longitudinal opinion surveys conducted over several years as case studies to investigate the application of clustering approach on LS (Longitudinal Studies). On each survey, they used standard statistical techniques to analyze and got some general conclusions on the population. According to their analysis, in case study 1,2 and 3, the agile development approach was in good shape. By applying clustering approach, we found that there are some important groups within the participants who have different opinions from the general conclusion. Some of the opinions remained over time during the survey period, while others missing.

This research may help software organizations as they can follow our approach to identify new ideas or critical opinions while conducting surveys within their respective domain. In our research, we analyzed a traditional data source, Opinion Survey, which is generally not considered for data mining (DM). Our study suggests this form of data may have some potential patterns which can be extracted through a clustering process. It may reveal new information and attract attention to alternative perspectives.

The remaining is structured as follows: Section 2 contains related work, in Section 3 we present the sample LS survey used for these case studies and provide methodology used, Section 4 shows results of analysis the longitudinal study using clustering, in Section 5 we discuss some issues related to our approach. Finally, in Section 6 we conclude with some future goals.

2. Related works

There are some standard guidelines to analyze such survey data, which are based on some rational investigation methods and simple statistical approaches. Kitchenham [4] & [6] described some of those methods with a caution for using advanced statistical methods like Bayesian analysis. They mentioned that "Bayesian methods are not usually used in software engineering studies" and recommends getting help from statisticians. Also, M. Mendonca and N. L. Sunderhaft [7], mention that the data mining has appeared as one of the tools to analyze software engineering data. Furthermore, they said data analysts should always consider statistics-based technologies as tools that can improve data mining.

In empirical software engineering, survey research has received less focus on a methodological level than other types of research. Wagner and other authors [8], compiled a list of significant and challenging topics in survey study. This ranges from how to use survey research to develop and test scientific hypotheses, to data analysis issues that consider both quantitative and qualitative data. Recently, John Moses [9], [10]& [11] has proposed a software quality prediction model based on expert opinion using Bayesian inference and Markov Chain Monte Carlo (MCMC) simulation. In general, descriptive statistical techniques, as well as hypothesis tests, are used to analyze survey opinion [12].

Mohammad M. H. and Martin B. [3] showed that applying DM on survey data has a good chance to discover different perspectives which may be overlooked and uninvestigated using traditional rational and simpler statistical analyses. Moreover, the utility of Longitudinal Study has been experienced in a few software engineering research studies. The efficiency of test-driven development was examined by Maximilien and Williams [13]. They performed a year-long study with an IBM software development group.

In [14], the strengths of agile development had been summarized as three points: focus on customer needs, adaptable to changing requirements and Fast development time. Jordan B. Barlow [15], mention that organizations that were adopting agile practices became more competitive, improved processes, and reduced costs and "some organizations are skeptical about whether agile development is beneficial".

3. Longitudinal case Study overview

From a single year survey in previous study [3], authors have defined an approach using clustering to identify and analyze interesting and minority groups with a diverse opinion. The clustering process starts with a low expected number of clusters and then increasingly the number of clusters. They identify cohesive and significant clusters in each step and labeled them. The process stops when no new significant groups appear. Because the size of identified groups may change in each step, authors recognize the groups based on their statistical closeness.

In our research, we used same approach on longitudinal survey data to analyze and detect agile skeptics over a period and reveal the minority whose voice may disappear when analyzing the survey by statistical analysis methods. We applied clustering to three case studies listed bellow, to ensure the effectiveness of clustering in extracting groups that represent the minority and have a different opinion and voice.

3.1 Case Study 1 (Project Success Rates Survey)

The survey was conducted by Scott W. Ambler a vice president and chief scientist for disciplined agile at project management institute, via Ambysoft Inc [16] . The purpose to know how IT professionals define project success rates in practice. It is an Opinion Survey (Project Success Rates Survey), conducted in several years 2008, 2011, 2013 and 2018.

In general, there are four success factors that determine the success of the project: schedule, money, functionality, and quality. In our research, we will focus in these four success factors for agile software development project.

The study was repeated in several years and in this study 2008, 2011, 2013 and 2018 were used. On average, 194 respondents each year was responded to the questionnaire. The questions used in our study are listed below:

- Q1: Time and Agile: When it comes to time/schedule, what is your experience regarding the effectiveness of agile software development teams (regardless of how distributed the team is)?
- Q2: Money and Agile: When it comes to effective use of money (return on investment), what is your experience regarding the effectiveness of agile software development teams?
- Q3: Functionality and Agile: When it comes to ability to deliver a system which meets the actual needs of its stakeholders, what is your experience regarding the effectiveness of agile software development teams?
- Q4: Quality and Agile: When it comes to the quality of the system delivered, what is your experience regarding the effectiveness of agile software development teams?

The motivation to why these questions were selected out of the rest of the questionnaire questions was the questions that focus on success factors that assess the successful of the development method used that is agile software development.

3.2 Case Study 2 (Agile Adoption Rate Survey Results)

The survey was conducted by Scott W. Ambler via Ambysoft Inc. The purpose to know the impact of Agile Techniques on agile and non-agile organizations. It is an Opinion Survey (Agile Adoption Rate Survey Results) [17], conducted in several years 2006, 2007, 2008 and 2014.

In our research, we will focus in four questions that measure impact of agile techniques on productivity, Quality of the systems produced, Cost of development and Satisfaction of business stakeholders.

The study was repeated in several years and in this study 2006 and 2008 were used, because the questions that was chosen for clustering were missing in rest years. In 2006, the questionnaire was responded by 4235 respondents. In 2008, responded by 642 respondents. The questions used for clustering are listed below:

- Q1: How have agile approaches affected your productivity?
- Q2: How have agile approaches affected the quality of the systems produced?
- Q3: How have agile approaches affected the cost of development?
- Q4: How have agile approaches affected the satisfaction of your business stakeholders in the work produced?

3.3 Case Study 3 (State Of The It Union Survey)

The survey was conducted by Scott W. Ambler via Ambysoft Inc. It is an Opinion Survey (state of the IT union survey) [18], conducted in several years 2009, 2014, and 2016.

The study was repeated in several years and in this study 2014 and 2016 were used, because the questions that was chosen for clustering were missing in 2009. In 2014, the questionnaire was responded by 231 respondents. In 2016, responded by 190 respondents. The questions used for clustering are listed below:

- Q1: How would you rate the team when it comes to: Return on investment?
- Q2: How would you rate the team when it comes to: Quality of work?
- Q3: How would you rate the team when it comes to: Stakeholder satisfaction?
- Q4: How would you rate the team when it comes to: Delivering on time?

The reason why these questions were selected was these questions focus on success factors that assess the successful of the development method used.

4. Analyzing Longitudinal Study

We used three longitudinal opinion surveys conducted over several years as case studies to investigate the application of clustering approach on LS (Longitudinal Studies). According to their analysis, in all case studies, the agile development approach was in good shape. By applying clustering approach, we can deconstruct survey to identify agile skeptics by observe that there are some important groups within the participants who have different opinions from the general conclusion. Some of the opinions remained over time during the survey period, while others may missing.

4.1 Analyzing Case Study 1 (Project Success Rates Survey)

Based on categorical data clustering from 2008 survey [16][3][3][3], we found two groups with diverse opinions (agile skeptics). For the longitudinal analysis, those two groups are used as the main groups. To identify those groups, we applied the same approach for other following years.

Finding an exact group based on the clustering process is a little difficult in a longitudinal analysis. The group identified in a particular year is extremely unlikely to reappear exactly in other years in terms of statistics.

In table 1 we show overall data distribution of survey questionnaires for years from 2008 to 2018. In figure 1, we show groups distribution over years for Case study 1. In the following sections, we will show each of those two groups in different years. We analyzed them to identify their changes over time.

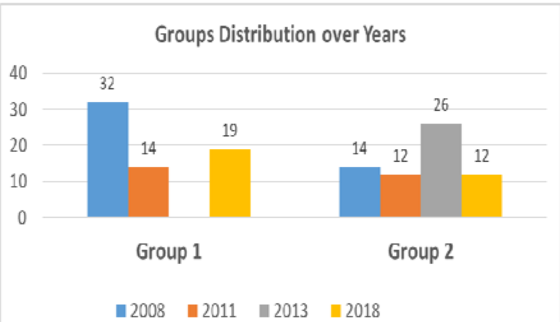

Fig. 1 Groups Distribution over Years (Case study 1)

4.1.1 Group 1

This group not only feels less confident regrading budget in agile but also feels the same regarding the quality of the system delivered process. Some distinctive properties of this group:

- 38% members are neutral regarding time/schedule at agile in 2008 .
- 50% suggests ineffective regarding time in 2011. We observe that all the members have more than 10 years' experience. Also, 47% members less confident regarding time in 2018 .
- 50% are less confident regrading budget at agile in 2008. Also, 29% in 2011. whereas 42% member was neutral regrading budget in 2018.
- 100% members who chose ineffective/very ineffective at ROI question in the general population in 2008 belongs to this group.
- 44% member was less confident regarding functionality in agile in 2008. Also, 50% in 2011, whereas 37% member was neutral in 2018.
- 44% was less confident regrading quality of the system delivered in agile in 2018.
- They are highly experienced; 88% have more than 10 years' experience in 2008, 79% in 2011 and 89% in 2018.
- 84% worked in orgs of 10+ IT people in 2008, 79% in 2011 and 58% in 2018.
- 53% work in technology organizations in 2008, 36% in 2011 and 37% in 2018.

4.2.2 Group 2

This group appears to be neutral with some of the success factors in Agile. It was existing during all 4 years. Some distinctive properties of this group:

- 64% consider agile is neutral regrading of time/schedule in agile in 2008. While in 2011, 2013 and 2018 their percentage became 50%, 36% and 75% respectively.
- 57% of members chose neutral regrading budget in 2008, whereas in 2011 and 2013 their percentage became 75% and 46% respectively.
- 86% suggests neutral regarding quality in 2008, 75% in 2011 and 42% in 2013.
- They are highly experienced; in 2008, 86% have experience more than 10 years. While in 2011, 2013 and 2018 their percentage became 83%, 69% and 93% respectively.
- In 2008, 64% work in IT organizations, while in 2011, 2013 and 2018 their percentage became 42%, 46% and 50% respectively .
- In 2008, 86% worked in orgs of 10+ IT people, while in 2011, 2013 and 2018 their percentage became 92%, 77% and 42% respectively.

4.2 Analyzing Case Study 2 (Agile Adoption Rate Survey Results)

Based on categorical data clustering from Agile Adoption Rate Survey Results in 2006 [17][3][3][3], we found one group with diverse opinions. As previous case study, this group is used as the main group for the longitudinal analysis. We applied the same approach to the other following year to track this group.

In general population of data survey in 2006, 91 respondents, (2.15%) had at least one very bad experience: 19 respondents, (0.45%) had much lower productivity. 18 respondents, (0.43%) had much lower quality. 73 respondents, (1.72%) had much higher cost. 20 respondents, (0.47%) had much lower business satisfaction.

709 (16.74%) of respondents had some negative experience: more than the above, 140 of respondents had slightly lower productivity. 64 respondents had somewhat lower quality. 539 respondents had somewhat higher cost. 59 respondents had somewhat lower business satisfaction. In table 2 we show overall data distribution of survey questionnaires in 2006 and 2008.

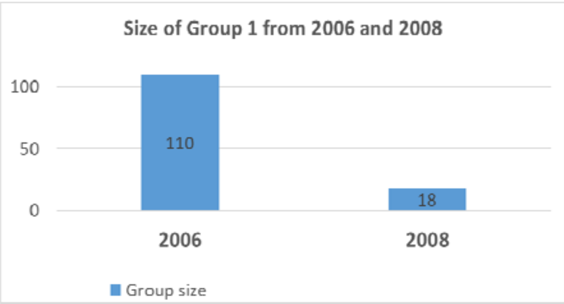

Fig. 2 Size of Group 1 in 2006 and 2008 (case study 2)

Table 1: Data distribution in general survey population- 2008 to 2018

Table 1: Data distribution in general survey population- 2008 to 2018

SQ	Answer	2008	2011	2013	2018	2008(%)	2011(%)	2013(%)	2018(%)
1) When it comes to time/schedule, what is your experience regarding the effectiveness of agile software development teams?	Very Effective	35	33	19	9	18.8	37.1	25.3	10.8
	Effective	42	30	28	31	22.6	33.7	37.3	37.35
	Neutral	19	9	13	13	10.2	10.1	17.3	15.66
	Ineffective	9	13	8	7	4.8	14.6	10.7	8.4
	Very Ineffective	4	1	0	4	2.2	1.1	0	4.8
	Not Applicable	77	3	7	0	41.4	3.4	9.3	0
2) When it comes to effective use of money (ROI), what is your experience regarding the effectiveness of agile software development teams?	Very Effective	34	33	24	14	18.1	37.1	32	16.87
	Effective	34	30	25	22	18.1	33.7	33.3	26.5
	Neutral	22	15	13	20	11.7	16.9	17.3	24.1
	Ineffective	12	6	3	3	6.4	6.7	4	3.6
	Very Ineffective	4	0	0	2	2.1	0	0	2.4
	Not Applicable	82	5	10	0	43.6	5.6	13.3	0
3)When it comes to ability to deliver a system which meets the actual needs of stakeholders, what is your experience regarding the effectiveness of agile software development teams?	Very Effective	60	41	34	15	32.1	46.1	45.3	18.1
	Effective	25	30	20	32	13.4	33.7	26.7	38.55
	Neutral	9	12	10	13	4.8	13.5	13.3	15.66
	Ineffective	13	3	3	3	7	3.4	4	3.6
	Very Ineffective	2	0	0	1	1.1	0	0	1.2
	Not Applicable	78	3	8	0	41.7	3.4	10.7	0
4) When it comes to the quality of the system delivered, what is your experience regarding the effectiveness of agile software development teams?	Very Effective	48	28	14	12	25.7	31.5	18.7	14.46
	Effective	30	32	34	36	16	36	45.3	43.37
	Neutral	15	18	14	9	8	20.2	18.7	10.8
	Ineffective	9	7	5	7	4.8	7.9	6.7	8.4
	Very Ineffective	6	1	1	0	3.2	1.1	1.3	0
	Not Applicable	79	3	7	0	42.2	3.4	9.3	0
Total population		188	89	75	84				

Table 2: Data distribution in general survey population- 2008 to 2018

SQ	Answer	2008	2011	2013	2018	2008(%)	2011(%)	2013(%)	2018(%)
1) When it comes to time/schedule, what is your experience regarding the effectiveness of agile software development teams?	**Very Effective**	35	33	19	9	18.8	37.1	25.3	10.8
	Effective	42	30	28	31	22.6	33.7	37.3	37.35
	Neutral	19	9	13	13	10.2	10.1	17.3	15.66
	Ineffective	9	13	8	7	4.8	14.6	10.7	8.4
	Very Ineffective	4	1	0	4	2.2	1.1	0	4.8
	Not Applicable	77	3	7	0	41.4	3.4	9.3	0
2) When it comes to effective use of money (ROI), what is your experience regarding the effectiveness of agile software development teams?	**Very Effective**	34	33	24	14	18.1	37.1	32	16.87
	Effective	34	30	25	22	18.1	33.7	33.3	26.5
	Neutral	22	15	13	20	11.7	16.9	17.3	24.1
	Ineffective	12	6	3	3	6.4	6.7	4	3.6
	Very Ineffective	4	0	0	2	2.1	0	0	2.4
	Not Applicable	82	5	10	0	43.6	5.6	13.3	0
3)When it comes to ability to deliver a system which meets the actual needs of stakeholders, what is your experience regarding the effectiveness of agile software development teams?	**Very Effective**	60	41	34	15	32.1	46.1	45.3	18.1
	Effective	25	30	20	32	13.4	33.7	26.7	38.55
	Neutral	9	12	10	13	4.8	13.5	13.3	15.66
	Ineffective	13	3	3	3	7	3.4	4	3.6
	Very Ineffective	2	0	0	1	1.1	0	0	1.2
	Not Applicable	78	3	8	0	41.7	3.4	10.7	0
4) When it comes to the quality of the system delivered, what is your experience regarding the effectiveness of agile software development teams?	**Very Effective**	48	28	14	12	25.7	31.5	18.7	14.46
	Effective	30	32	34	36	16	36	45.3	43.37
	Neutral	15	18	14	9	8	20.2	18.7	10.8
	Ineffective	9	7	5	7	4.8	7.9	6.7	8.4
	Very Ineffective	6	1	1	0	3.2	1.1	1.3	0
	Not Applicable	79	3	7	0	42.2	3.4	9.3	0
Total population		188	89	75	84				

4.2.1 Group 1

This group shows different opinion from general population, they show that the effect of agile techniques on them was negative and ineffective. Figure 2 illustrate the size of group over years. Also, table 3 illustrate distribution of this group in two years. Some of the characteristics of this group are:

Table 3: Data distribution in general population (Case study 2)

How have you been affected by agile?	Answers	2006	2006 in %	2008	2008 in %
Productivity	Higher	1640	43.1%	271	42.3%
	No change	911	22.9%	44	6.8%
	Lower	159	4%	19	2.9%
	Don't know	1267	31.9%	16	2.5%
	No Answer			290	45.3%
Quality of the systems produced	Higher	1767	44.4%	257	40.2%
	No change	829	20.8%	46	7.2%
	Lower	82	2%	30	4.7%
	Don't know	1299	32.7%	17	2.7%
	No Answer			290	45.3%
Cost of development	Higher	612	15.4%	66	10.3%
	No change	1343	33.8%	116	18.1%
	Lower	551	14%	109	17%
	Don't know	1471	37%	59	2.6%
	No Answer			290	45.3%
Satisfaction of business stakeholders	Higher	1503	37.8%	246	38.4%
	No change	1013	25.5%	46	7.2%
	Lower	79	2%	20	3.1%
	Don't know	1382	34.7%	38	5.9%
	No Answer			290	45.3%
Total		4235		640	

- In 2006, 70% of respondents belong to this group had lower productivity while in 2008 it was 67%.
- In 2006, 59% of respondents belong to this group had lower quality while in 2008 it was 89%.
- In 2006, 61% of respondents belong to this group had higher cost whereas in 2008 it was 89%.
- In 2006, 51% of respondents belong to this group had lower business satisfaction whereas in 2008 it was 56%.

We observed that when this group appeared in 2008, their number was smaller, but the percentage of negative impact they had seen from agile techniques that applied in their organizations increased than in 2006. Also, there was a correlation between experience and results, the respondents who not experienced with agile methods had bad impact than those who were experienced.

Table 4 : Data distribution of Group1 in 2006 and 2008 (Case study 2)

How have you been affected by agile?	Answers	G1 in 2006	G1 in %	G1 in 2008	G1 in %
Productivity	Higher	5	4.5%	0	0
	No change	23	20.9%	6	33.3%
	Lower	78	70.9%	12	66.7%
	Don't know	4	3.6%	0	0
Quality of the systems produced	Higher	10	9.1%	0	0
	No change	25	22.7%	2	11.1%
	Lower	65	59.1%	16	88.9%
	Don't know	10	9.1%	0	0
Cost of development	Higher	67	60.9%	16	88.9%
	No change	8	7.3%	1	5.6%
	Lower	29	26.4%	0	0
	Don't know	6	5.5%	1	5.6%
Satisfaction of business stakeholders	Higher	11	10%	4	22.2%
	No change	29	26.4%	4	22.2%
	Lower	56	50.9%	10	55.6%
	Don't know	14	12.7%	0	0
Total		110		18	

4.3 Analyzing Case Study 3 (State of The IT Union Survey)

Based on categorical data clustering from State of the IT Union Survey Results in 2014[3][3] [18], we found one group with diverse opinions. As previous case study, this group is used as the main group for the longitudinal analysis. In table 4 we show overall data distribution of survey questionnaires for years from 2014 and 2016.

4.3.1 Group 1

This group shows different opinion from general population, they show that the effect of agile techniques on them was negative and ineffective. Some of the characteristics of this group are:

- In 2014, 40% of respondents had lower confidence regarding return on investment while in 2016 it was 84%.
- In 2014, 21% of respondents belong to this group had lower quality while in 2016 it was 63%.
- In 2014, 46% of respondents had neutral about stakeholder satisfaction whereas in 2016 it was 42%.
- There was a large percentage 55% of respondents had less confidence regarding delivering on time at agile projects.

We notice that in 2016, there was small group but more skeptics there had been.

Table 5: Data distribution in general population (Case study 3)

How would you rate the team when it comes to:	Answers	2014	2014 in %	2016	2016 in %
Return on investment	Very Good	22	13.33%	16	12.4%
	Good	69	41.8%	48	37.2%
	Neutral	35	21.2%	29	22.5%
	Poor	21	12.7%	20	15.5%
	Very poor	6	3.6%	4	3.1%
	Don't know	12	7.3%	12	9.3%
Quality of work	Very Good	35	21.2%	17	13.2%
	Good	81	49.1%	73	56.6%
	Neutral	33	20%	22	17.1%
	Poor	15	9.1%	10	7.8%
	Very poor	1	0.6%	4	3.1%
	Don't know	0	0	3	2.3%
Stakeholder satisfaction	Very Good	37	22.4%	20	15.5%
	Good	76	46.1%	63	48.8%
	Neutral	30	18.2%	27	20.9%
	Poor	16	9.7%	11	8.5%
	Very poor	2	1.2%	2	1.6%
	Don't know	4	2.4%	6	4.7%
Delivering on time	Very Good	24	14.6%	18	13.9%
	Good	58	35.2%	54	41.9%
	Neutral	38	23%	29	22.5%
	Poor	40	24.2%	19	14.7%
	Very poor	3	1.8%	6	4.7%
	Don't know	2	1.2%	3	2.3%
Total		231		190	

Table 6: Data distribution of Group1 in 2014 and 2016 (Case study

How would you rate the team when it comes to:	Answers	G1 In 2014	2014 in %	G1 in 2016	2016 in %
Return on investment	Very Good	2	3%	0	0
	Good	11	16.7%	0	0
	Neutral	20	30.3%	3	15.8%
	Poor	21	30.8%	13	68.4%
	Very poor	6	9.1%	3	15.8%
	Don't know	6	9.1%	0	0
Quality of work	Very Good	8	12.1%	0	0
	Good	20	30.3%	2	10.5%
	Neutral	24	36.4%	4	21.1%
	Poor	13	19.7%	9	47.4%
	Very poor	1	1.5%	3	15.8%
	Don't know	0	0	1	5.3%
Stakeholder satisfaction	Very Good	2	3%	0	0
	Good	15	22.7%	0	0
	Neutral	30	45.5%	8	42.1%
	Poor	16	24.2%	9	47.4%
	Very poor	2	3%	2	10.5%
	Don't know	1	1.5%	0	0
Delivering on time	Very Good	1	1.5%	0	0
	Good	8	12.1%	3	15.8%
	Neutral	18	27.2%	4	21.1%
	Poor	36	54.5%	7	36.8%
	Very poor	3	4.5%	5	26.3%
	Don't know	0	0	0	0
Total		66		19	

5. Discussion

Anderberg shown that, by simple human ability, it is very difficult to understand possible partitions from dataset. He gave an example where a possible grouping of 25 observations into 5 groups is huge (exactly 2,436,684,974,110,751) []. For a small survey, it is almost impossible to overall divide the population manually and explore their characteristics. The problem becomes more complex in case of longitudinal studies where the additional data. On the other hand, similar problems in other domains can be solved by clustering. Figure 4 [3], shows the process flow graph which discusses some impeding important factors of the process.

In the current study, clustering techniques had applied in a systematic manner to partition the survey population, then identify significant groups who showed alternative opinions and analyze them. Our initial finding suggests that though overall "Agile practices" among the groups are satisfactory, but there is a group which has significantly in lower confidence level.

Process with examples already was discussed the in previous study [3]. In this chapter, we discuss some of the important factors that may constrain the clustering. Data preparation is an important step before beginning the mining process because some clustering algorithms are not configured to handle missing data, so empty records must be eliminated or to be filled with some suitable data to distinguish them from others.

Certainly, some variations in questions at each survey are expected in case of longitudinal study, which may affect the analysis process. For example, in case study 1, there was differences in the form of survey in 2007 and 2010, that why it excluded from analysis. In our research, we focus on a common set of questions across surveys at each case study.

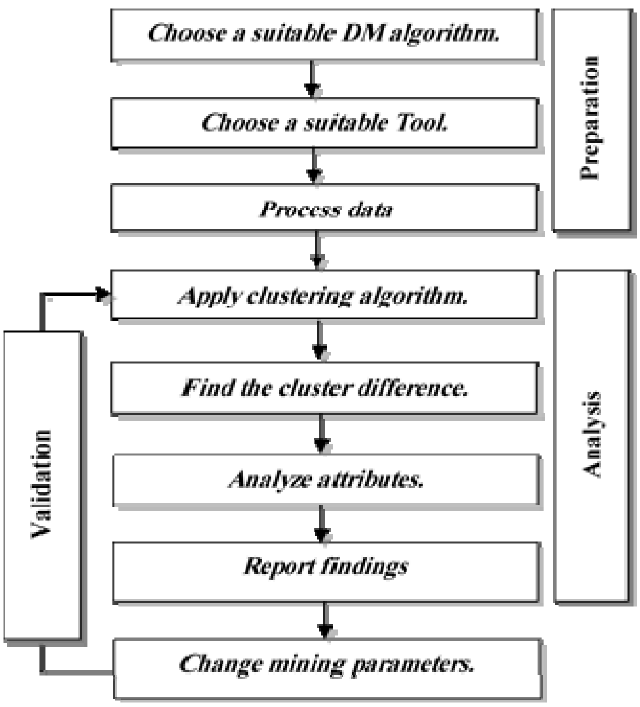

Fig. 3 process Flow

3. Conclusion & Future Work

Opinion-based surveys in software engineering usually analyzed using descriptive statistical tools which have overall conclusions. The small number of participants may lead to a researcher being excluded for using data mining as an analysis tool, that's why there is rare of using data mining tools in this kind of data.

In the case of longitudinal studies, where minority opinions might fade or resolute over time, the problem becomes more complex. We suggest using a data mining approach to finding the diversity among the different groups in longitudinal studies. Longitudinal survey data may contain some potential patterns that can be extracted using a clustering process. It may reveal new information and attract attention to alternative perspectives. Our main objective in this research is to demonstrate that in longitudinal studies there are strong alternate opinions that can be revealed and tracked over time, and clustering approach can expose them. Also, this give the minorities an opportunity to be heard. In the future, we will propose a systematic process structure which can be used to analyze software engineering longitudinal studies using clustering techniques.

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