Intelligent Systems: Implications of Satisfaction and Trust in Social Media

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Abstract

Social media has become a ubiquitous platform for communication, reliance, and information sharing. This highly interactive forum is noticeably different from other websites in the internet. Likewise, intelligent technologies in the social media has revolutionized the way of interaction in internet and beyond. This paper attempts to understand, how the behavior of the intelligent systems, impact on the trust and satisfaction perceived by the users of social media. Multiple data sources such as, online discussion group, online focus group and traditional focus group were used to collect data. Further, thematic analysis was used to find the patterns and themes within the data. Based on the results, I argue that satisfaction and trust can be reinforced by giving enough control to the user and by concentrating more on the intuitive behavior of the intelligent systems. Consequently, the results can help researchers and social media firms to enable better social media experience.

Keywords: Adaptive User interfaces, Mixed-Initiative systems, Social Media, Satisfaction, Trust

Introduction

Social media has become a ubiquitous platform for communication, reliance, and information sharing. Co-creating, Sharing, Connecting and modifying user-generated contents are the distinguished features of social media among others (Kietzmann, Hermkens, McCarthy, & Silvestre, 2011). Nevertheless, many concerns have arose regarding the SNS (Social Network Sites), such as addiction, cyberbullying, tracking and tracing, privacy, and connections with dangerous communities. (O'Keeffe & Clarke-Pearson, 2011; Bhat, 2008; Nissenbaum, 2010; Sánchez Abril, Levin, & Del Riego, 2012; Hansen, Shneiderman, & Smith, 2011). These discussions are related to interactions among communities and not between the users and intelligent systems. Therefore, the focus of this paper is to understand the role of interaction between the users and the system, in social media platform.

In user experience paradigm, trust is a very important component ("Trust in Experience Design | UX Magazine", 2016; Carminati, Ferrari, & Viviani, 2013, p. 27). Likewise, satisfaction is another component, which governs the experiential part of the usability (Nielsen, 1993). Both trust and satisfaction have an important role in delivering a great user experience (Bevan, 2009). Therefore, the goal of this paper is to discuss the implications of satisfaction and trust, when humans and intelligent systems in social media work together. As most of the social media websites implement intelligence, either in the interface or in the system, this study could help in designing great social media experiences.

The paper is structured as follows. First, I discuss the intelligent systems and its implications on satisfaction and trust. Then, I discuss the data collection and analysis part. This involves three different data sources; online focus groups, traditional focus groups and data mining from the online discussion groups. Next, the results are presented in the form of themes that emerged during thematic analysis. Further, I discuss the themes themselves and their implications with respect to the existing theories. Finally, I discuss the need for future work based on the research findings.

Literature Review

User experience plays an important role in the social media design (Asad, 2009). Social media is different from conventional websites and involves numerous interactions. Designing great experiences in such websites can be challenging. The concept of user experience is not simple as it involves various facets (Hassenzahl & Tractinsky, 2006; Rosenzweig, 2015; Chesnut & Nichols, 2014). First, I scope the user experience to current context, then I discuss satisfaction and trust. Next, I talk about intelligent systems in social media and arrive at research questions.

User Experience

ISO FDIS 9241-210 defines user experience as

"A person's perceptions and responses that result from the use and/or anticipated use of a product, system or service"

Nielson (1993) characterizes satisfaction in usability as user experience. Please note that user experience is not this simple (Hassenzahl & Tractinsky, 2006). UX also involves emotion, trust, experiential aspects and concepts that are beyond instrumental components. This is referred as the facets of UX (Hassenzahl & Tractinsky, 2006). However, this article focuses mainly on the satisfaction and trust components of the user experience.

Satisfaction and Trust

Satisfaction is the pleasure component of the usability (Nielsen, 1993). According to Bevan (2009), the satisfaction is comprised of sub-components such as likeability, pleasure, comfort, and trust. In some cases, satisfaction and trust are measured separately, which is referred as perceived usability (Flavián, Guinalíu, & Gurrea, 2006).

Further, perceived risk in the social media has negative influence on the social media usage (Currás‐Pérez, Ruiz‐Mafé, & Sanz‐Blas, 2013). Accordingly, perceived risk can be correlated to trust (Corritore, Kracher, & Wiedenbeck, 2003; Maes, Shneiderman, & Miller, 1997). However, discussions by Corritore et al. (2003) and Maes et al. (1997) takes e-commerce website into consideration, where trust is built upon the product and money transactions. But social media has significant other purposes, along with product marketing (Mangold & Faulds, 2009). Therefore, this paper tries to understand the implications of satisfaction and trust in the context of intelligent technologies. In the next section, I discuss intelligent technologies.

Intelligent Technologies

The definition of Intelligent technologies varies based on the context. In some cases, technology which undertakes significant amount of cognitive activity is considered as intelligent technology (Salomon, Perkins, & Globerson, 1991). For example, a simple calculator in the windows operating system is an intelligent technology. In other cases, intelligent technologies are referred as technologies with artificial intelligence (Pollack, 2005). For example, recommender systems in social media can have machine learning components, hence, this is an intelligent technology. Therefore, when I refer to intelligence or intelligent technology in this paper, it comprises of both AI as well as non-AI components.

There are discussions on the implications of intelligent technologies on thinking, learning and solving problems (Pea, 1985; Allen, Guinn, & Horvtz, 1999; Ferguson & Allen, 2007). But, these discussions do not take the usability criteria into account. Further, Perugini & Ramakrishnan (2003) claim that personalizing the user's interaction is one of the best ways to establish collaboration between humans and intelligent technologies. There are discussions on such collaborative technologies in social media context (Guy, Zwerdling, Ronen, Carmel, & Uziel, 2010), but they do not consider trust and satisfaction into account. Therefore, I outline collaborative technologies such as Mixed-Initiative systems, Adaptive user interfaces and recommender system in research context.

Mixed-Initiative systems

Mixed-initiative approach promises to dramatically enhance human-computer interaction by allowing computers to behave more like associates. They are able to work with users to develop a shared understanding of goals and help in problem-solving in the most appropriate and collaborative way (Horvitz, 1999). Collaboration means working together as a group. Taking initiative means, the ability to direct the group's behavior. A mixed-initiative system is one that allows the participants to separately contribute what they can to the group's overall success (Ferguson & Allen, 2007). Intelligent technologies in social media forms a partnership with users to sense their activities and help them in their tasks (Carminati, Ferrari, & Viviani, 2013). The discussions on trust factors of political actors in social media leverages topics of mixed initiatives (Calderon et al., 2015). However, this discussion does not highlight the trust between the intelligent technology and the user. There is a discussion about the efficiency and effectiveness of mixed-initiative systems (Horvitz, 1999; Ferguson & Allen, 2007; Perugini & Ramakrishnan, 2003; Allen, Guinn, & Horvitz, 1999), but they do not discuss trust and satisfaction in such systems. Further, there are discussions of collaboration between the user and system in social media, which constitutes mixed initiatives (Kautz, Selman, & Shah, 1997). But, the scope is limited to system’s behavior and functionalities.

Adaptive User Interfaces

Social media as mentioned before is a complex system compared to other websites found in the internet. Apart from the involvement of mixed-initiative systems, it also leverages adaptive systems to perform.

According to Browne, Totterdell, & Norman (1990),

"An adaptive user interface is an interface which can change its behavior to suit an individual or group of individuals".

In the social media, to aid search and discovery mechanisms and identify relevant posts, tags and people (Leung, Chan, Milani, Liu, & Li, 2012) adaptive user interfaces have been implemented. There are researches based on the adaptive user interface and its role in providing solution to usability problems (Benyon, 1993). Localization of user interfaces based on the region and culture in social media are based on adaptive systems as well (Bourges-Waldegg & Scrivener, 1998). Further, Reinecke & Bernstein (2011) discuss about improving performance, perceived usability, and aesthetics with adaptive user interfaces on cultural platform. The adaptation to user in the adaptive interfaces, albeit based on the users are automatic in nature (Browne, Totterdell & Norman, 1990). This poses a problem since it violates the usability heuristics for UI design (Nielsen, 2016), where users prefer to have control over interfaces. This violation of user control and freedom can impact the satisfaction perceived by the users (Nielsen, 2016)

Recommender Systems

It is not uncommon for the users of social media to encounter recommender systems. They help users to make better choices from the mammoth content catalogs, entertainment related items such as movies, jokes, news, even insurance policies (Xiao & Benbasat, 2007;

Resnick & Varian, 1997). These recommendations are based on the algorithms which derives the user's preferences from implicit or explicit feedback (Pommeranz, Broekens, Wiggers, Brinkman, & Jonker, 2012). According to Golbeck & Hendler (2006), Semantic Web-based social networks which are enhanced with trust to create recommendations are more accurate in certain cases. However, trust in this research is subjective to users, instead of trust between intelligent system and the user. The user experience in recommender systems can be improved by user-centered development (McNee et al. 2006) and evaluation (Pu, Chen, & Hu, 2012; Pu, Chen, & Hu, 2011). There is discussion about the recommender system's ability to establish trust with the users and convince them of the recommendations provided by the systems (Pu & Chen, 2007), but this does not the cover the establishment of trust or how users perceive the recommendation systems, or the intelligent system together as a whole.

Since the intelligent systems plays an important role in managing the content, keeping track of the users' interests, it is very important to identify the implications that are necessary for users to have great user experience. This brings us the following research questions.

1. What are the characteristics of Intelligent systems that influence the satisfaction in Social media?
2. How do users perceive the behavior of intelligent systems in social media?
3. How do users perceive trust factor due to intelligent systems in social media?

In the next section, I will discuss about the methods that were involved in gathering the data in support of this research, and answering the above research questions.

Research setting and methodology

Data Collection

In order to gain the detailed understanding of how users perceive the actions of intelligent systems in social media, I collected data from three main sources.

1. Traditional focus group
2. Online focus group.
3. Data mining from the discussion groups.

These multiple data sources can aid in the triangulation (Fielding & Fielding, 1987) as a criterion for validity (Maxwell, 2013). It also helps in reducing the risk of biases from a specific method. This can also help in gaining information about different aspects of the phenomena under study or even the different phenomena themselves (Maxwell, 2013). This is referred to as complementarity and expansion (Greene, 2007, pp. 101-104).

Traditional focus group

The primary reason for choosing focus group is, it is socially constructed rather than individually created (Berg & Lune, 2011). Since interviews depend heavily on the memory, and social media encounters that I am studying is situation based, focus group is more suitable. Also, focus group interviews are very useful in a triangulated project (Stewart, Shamdasani, & Rook, 2007) such as the current research. According to Berg & Lune (2011),

"In focus groups, the goal is to let people spark off one another, suggesting dimensions and nuances of the original problem that any one individual might not have thought of. Sometimes a totally different understanding of a problem emerges from group discussion" (p. 174).

Hence, the discussion and nature of brainstorming of Focus group can aid in providing a collective data that is required to study the emerging themes. This rakes advantage of the fact that people naturally interact and are influenced by others (high face validity).

All the five participants recruited were master's students from Purdue University. They were recruited based on criterion sampling, where the criterion was frequent usage of social media. The participants who used social media for more than 2 hours a day were regarded as frequent users. The social media which were frequently used involved Facebook, Twitter, and YouTube. They were also recruited based on convenience and snowball sampling (one participant referred to another).

Online focus group

Asynchronous group communications were used in order to collect data from the computer-mediated group interactions (Stewart, 2005). The interactions in this type of focus group was text based. Participants had option of uploading video, but they did not choose to use this option. The participants' origin was unknown, but their gender and field of occupation was captured. Free Online Focus Group Software – FocusGroupIt (2016), was used for this purpose. Twelve participants were recruited through advertisement in the Facebook groups by using the invitation link provided by FocusGroupIt. Bias of replies were taken care by blocking the answers from other participants until an answer for specific question is delivered. Once the participants answered the questions, they were given access to comment and an option to extend their previous comment. This ensured the brainstorming quality of focus group along with reducing the reply bias. Samples were recruited based on the survey, which determined the social media usage of the participants. The usage is again determined by the survey, similar to the one conducted in traditional focus group.

Data-mining from discussion groups

Xin Chen, Vorvoreanu, & Madhavan (2014) talk about how people perform in the relaxing atmosphere of backstage compared to the front front-stage. When an article is posted on the internet, readers comment only when they feel the need for commenting on it. They do not have any compulsion of providing the comment unless they identify themselves with the situation (Chai, Hayati, Potdar, Wu, & Talevski, 2010; Andrews, 2002). I collected the data from about four different websites where people commented voluntarily.

1. The Guardian (Solon, 2016), where the post was about a recent update on Facebook to better understand the people
2. Google Product Forums ("Google Groups", 2016) on YouTube, where there was a discussion on YouTube recommender system
3. ProPR website (Thornley, 2015), where there was a post about Facebook newsfeed.
4. Change.org ("Keep Instagram Chronological!", 2016), where there was a post on the recent (2016) recommender system update on Instagram

The above websites where chosen because they are popular and have large amount of users. The posts in the websites were related to the intelligent systems in social media, without using the words AI or intelligence. Homogeneous sampling was used to select similar cases to investigate topic relevant to research. Along with this, stratified random sampling was used to choose the comments from the discussion (Patton, 2010). In the next section, I discuss the results and data analysis in detail.

Results

The results were derived from three different data sources. One of the major data source in the research was discussions from the four different websites. The discussions were related to recent changes in social media platforms. For example, the post in the Change.org ("Keep Instagram Chronological!", 2016) was about the recent change in Instagram.

A total of 664 unique comments were sampled from these forums for analysis. Out of which the regional demography of the post on Instagram was available. This large sample size from all over the world helped in eliminating geographical biases (Henry Wai-Chung, 2001). The results are based out of 34 different countries, and each comment was carefully analyzed multiple times, to categorize into different codes. Refer to Table 1 and Table 2 for more details.

Table 1

Comments from four different websites

Data Source	Number of unique comments
1. The Guardian (Solon, 2016), where the post was about a recent update on Facebook to better understand the people	20
2. Google Product Forums ("Google Groups", 2016) on YouTube, where there was a discussion on YouTube recommender system	90
3. ProPR website (Thornley, 2015), where there was a post about Facebook newsfeed.	45
4. Change.org ("Keep Instagram Chronological!", 2016), where there was a post on the recent (2016) recommender system update on Instagram	512
Total	664

Table 2

Regional Demography for comments in Change.org

Country	Number of unique comments
1. USA	263
2. Australia	67
3. United Kingdom	60
4. Canada	28
5. Netherlands	8
6. Norway	7
7. Denmark	6
8. France	6
9. Sweden	6
10. Germany	5
11. Brazil	4
12. Ireland	4
13. South Africa	4
14. Czech Republic	4
15. Finland	3
16. Portugal	3
17. New Zealand	3
18. Singapore	3
19. Philippines	3
20. Malaysia	2
21. Austria	2
22. Italy	2
23. Ukraine	2

24. Venezuela	2
25. Belgium	2
26. Spain	2
27. Russia	2
28. China	2
29. India	2
30. Serbia	1
31. Hungary	1
32. Peru	1
33. Estonia	1
34. Slovenia	1
Total	512

For the second data source, which is online focus group discussion, about 17 people were sampled. Out of which only 12 completed the discussion with full participation. Hence, data related to only those 12 participants were considered for the analysis. There were 4 females and 8 males who participated in the online focus group and discussion was asynchronous. The participants' regional demography was unknown. All the participants mentioned they were from either IT industry background or from the engineering background. The discussion was conducted for about 5 days, where participants answered questions on a daily basis. Participants responded the questions, without knowing the answer of other participants, until they answered them. Later, they commented on other's answer as well as extend their own. This helped in reducing the bias, as well as preserving the brainstorming nature of focus group. Refer to Figure 1 for example.

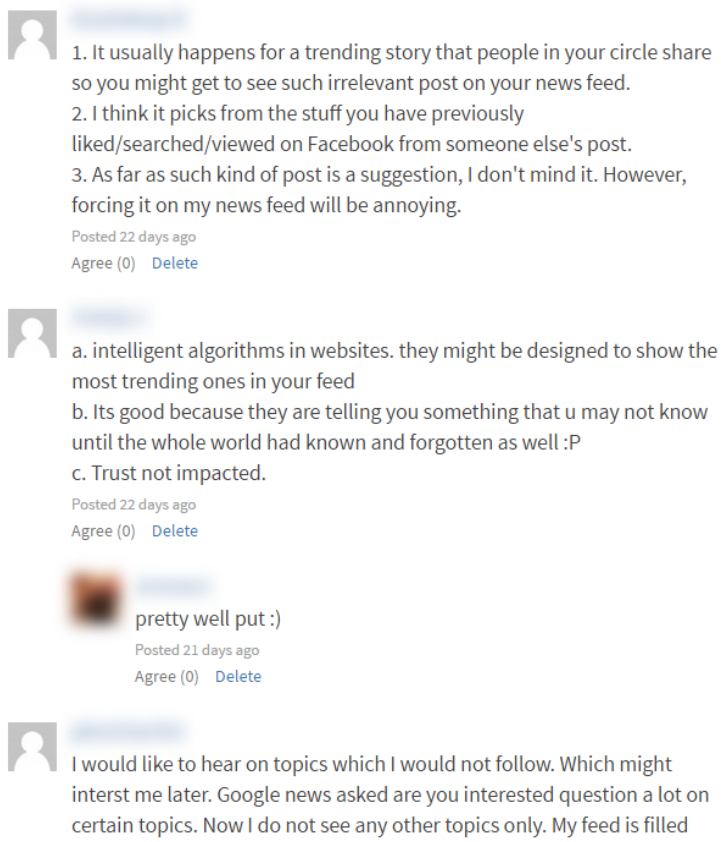

Figure 1. A screen shot from the online focus group responses.

For traditional focus group discussion, I sampled five participants, who were all master's student from Purdue university. All the participants were male, and they were either from science or engineering background. A pre-interview questionnaire was sent online to 12 students, out of which, 5 students responded. All the participants declared themselves as frequent users of social media, hence they were recruited for the participation. Refer to table 3 for the participant responses and details from the survey.

Table 3

Participant information from the pre-interview survey

Participant	Gender	Age	Frequency of usage	Hours of usage per day	Frequently used social media	Least used social media	Participant's area of study
P1	Male	25	Daily	Greater than 8	Facebook, YouTube	Quora	Computer Science
P2	Male	25	Daily	4-6	Facebook, YouTube	Pinterest, Twitter	Computer Engineering
P3	Male	25	Daily	2-4	Facebook, YouTube	Pinterest	Computer Science
P4	Male	24	Daily	4-6	Facebook, YouTube, Twitter	Details unknown	Computer Science
P5	Male	23	Daily	1-2	Facebook, YouTube	Details unknown	Aeronautics and Astronautics Engineering

I acted as moderator for the focus group and it took about 46 minutes to finish the focus group discussion. Ground rules were laid in the discussion to reduce the bias and clutter, that tends to happen in the focus group. Before starting the focus group discussion, all participants were informed about the purpose of the discussion, confidentiality, and practical issues. I explained that focus group is similar to brainstorming sessions since they were not aware of focus group itself. I also asked them to take turns and not to interrupt, when other participants are speaking. All the participants were asked to switch off the electronic devices till the focus group lasted. I ensured that all participants had fair chance to talk and they responded and contributed equally in the discussion. Steps were taken not to lead the discussion in any desired direction, and an assistant was present to jot down the notes during the discussion. The discussion was digitally recorded and transcribed to extract the codes.

In the focus group session, I started with social media usage of the participants. Next, we discussed about the frequent and infrequent posts, newsfeeds, and recommendations provided by social media. Participants referred to multiple social media in their discussions. It included Facebook, Twitter, Instagram, Quora, YouTube, Pinterest, Songza, Reddit, Vimeo, Verge and Google Now cards. I ran through some scenarios to trigger discussions on expected and unexpected posts and newsfeeds on social media. We discussed about the frustrations and some questions directly expected the participants' take on satisfaction and trust on certain scenarios. Finally, the discussion was ended with open-ended question. More details can be found in Appendix A section of this paper.

Data analysis

I used thematic analysis as a method to identify, analyze and report the patterns or themes that emerged within the data (Braun & Clarke, 2006). The data was coded using the QSR - NVIVO software, by reading through the data sets that were uploaded into the software. Interesting features were coded in systematic fashion across the entire data set and they were collated to relevant code. The codes were further organized into post-it notes, naming each code. These codes were further categorized into themes. Eighty-nine codes were generated together from three data sources. All the codes were arranged by using affinity diagramming (Nayak, Mrazek, & Smith, 1995) to ease the re-arrangement and to find the patterns.

Initially, nine subthemes were found from the different data sources. These subthemes were categorized based on the relevance to form four major themes. Refer to Table 4 for the detailed set of codes and theme categorization that emerged from the thematic analysis and Figure 2 for the code categorization using post-its.

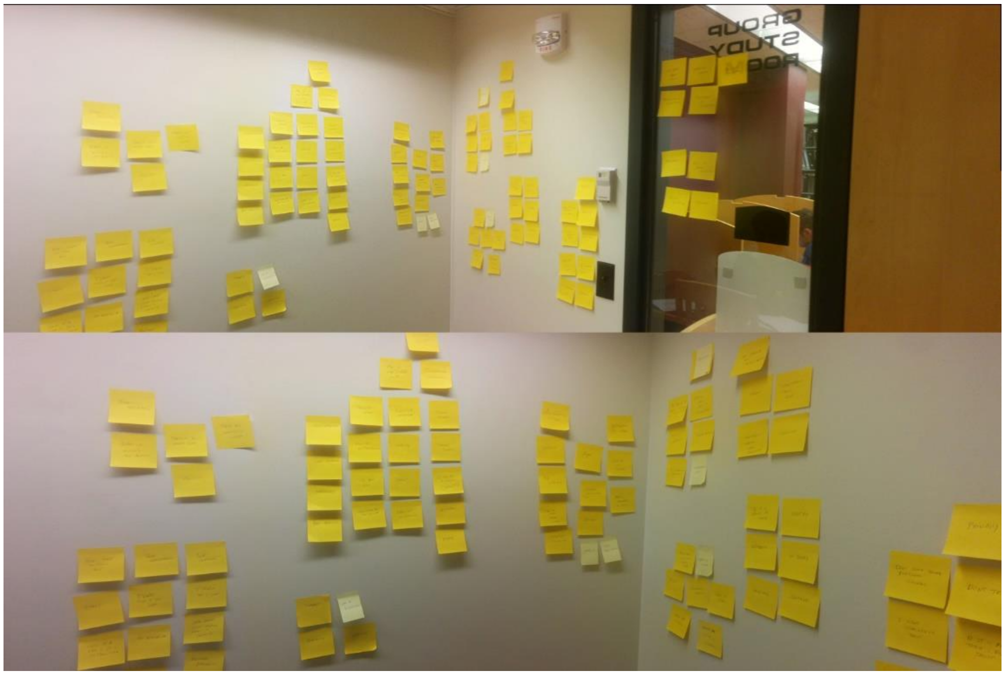

Figure 2. Codes were categorized into themes using affinity diagramming.

Table 4

Findings of the research represented in themes

Themes	Sub-themes	Codes
Reason for social media usage		21
How people perceive intelligence in social media	How people identify intelligent systems	6
	Behavior of Intelligence in social media as perceived	6
	Positive aspects of intelligent systems	11
Trust implications due to Intelligent systems	Privacy factors	10
	Uncanny characteristic of Intelligent systems	10
	Boundary or leading characteristic of intelligent systems	4

Factors that influence satisfaction	Implications due to the control and autonomy	8
	Other factors that influence satisfaction	13

The next section is a brief discussion about each of the themes that emerged during the analysis.

Themes

Four main themes emerged from the thematic analysis out of 89 codes. Three of those themes have sub-themes which explains the main theme in more detail.

Reason for social media usage

Participants expressed various reasons for using social media. For most users, the main reason for selecting social media was available content and amalgamated information. Amalgamation means, mixture of different genre of information. They viewed social media as starting point to explore different activities such as entertainment, fun, news, knowledge platform, job, and even marriage. They also mentioned that keeping up with friends is important. Most people chose social media based on the number of common friends they had in that particular platform.

“right now, everyone is like what did you do on Facebook, like you shared this pic. if you don’t use it, there is no life according to me”

Few participants viewed social media as way of passing time and it has become habitual. Most of the participants mentioned that their selection of social media greatly depends on the usability and relevant content. Here relevant content refers to, the content users expect from particular social media website. In the research diverse group of people were sampled, hence it covered all the major aspects of usage of social media.

How people perceive the intelligence in social media

This theme summarizes the people’s perception about the intelligence in social media. The subthemes explain how people view and identify the intelligent systems, how people perceive the behavior of intelligent systems and the positive aspects of social media.

How people identify intelligent systems

Based on the analysis from the research sets, it was found that even though most people do not use the word *Artificial Intelligence*, they refer it using different indicators.

“However, if I am extremely bored and I do look at it and get irritated, it is possible that the feed reappears, because for some "coded" reason”

This indicates that although the participants did do not know about the exact mechanism, they still perceive the intelligent systems in the social media. Out of many posts that appear on the social media pages, many people thought it was due to a chance while others perceived it as deliberate act of mysterious coding. This can be further explained by discussing the behavior of intelligent systems in social media.

Behavior of Intelligence in social media as perceived

Participants associated the behavior of social media with the advertisement and newsfeeds that appears on social media website. These advertisements and newsfeeds are often relevant to user and his/her preferences. It is also common in many platforms, where after choosing to unfollow a topic, the system asks for the feedback. Most people found this irritating, blaming intelligent systems for not being intuitive enough. The mixed-initiative systems are built upon the feature of understanding the user and collaborating with minimal intervention. This has greater impact on the satisfaction, which is discussed under separate theme.

“It should be intelligent enough to think about different parameters, like how long you are seeing those videos, did you see entire video, all the actual parameter should tell what the person is interested in”

There is also a greater expectation towards intelligent systems in understanding the emotions and moods of the users. People perceive the intelligent systems as too mechanical, where the results given by intelligent systems are viewed as being unemotional.

“Basically, it is not jumping to conclusions, it should not keep throwing a lot of questions to your faces”

Positive aspects of intelligent systems

The participants did not just blame the social media relentlessly. There were many positive aspects that was associated with the intelligent systems in social media as well. Many praised the recommender systems of Facebook as very good engineering.

“I prefer to let the algorithms do their magic because I follow a lot of news sites, but have more than a few friends who--let's be honest--really don't have interesting things to say”

Some users wanted social media to do its job by offering interesting content. They more interested in the randomness in posts and feeds, so that they can follow new topics. They mentioned that Quora does this job very well, and they spend lot of time there. Some users also told, that people should wait, before the social media adapts to the user. Initially, it will ask lot of questions and throw irrelevant questions, but later they improve. They were also used to allowing the recommender systems do the job.

However, some pointed this out as problem as well. They wanted the system to understand the mood and preferred to have the choice for choosing news feed or allow the users to choose the topics of interest. Many mentioned that they were well aware of all the implications of social media, such as privacy and trust, and they are so used to the system, hence they do not care about all this anymore. This can be referred to as habituation of the people, where they undermine certain dangers.

Trust implications due to intelligent systems

This theme discussed about the implications of trust in social media due to intelligent systems. All three subthemes expressed concerns about trust, hence, they were organized under single theme. The three themes are privacy factors, uncanny characteristic of intelligent systems and Boundary or leading characteristic of intelligent systems.

Privacy factors

"I would like my data and my browsing history to be secure and not be used to develop patterns"

Privacy has huge implication in social media (Barnes, 2006). Most people did not like the intelligent systems invading the personal data. They mostly were fine with the intelligent systems giving suggestions, adaptive intelligent systems changing the interfaces, as far as it was not related to exposing their personal data. They also had certain level of trust set to each social media website. This is what I would to call as selective trust in the social media.

"Trust wise know, Facebook and all I know it is just time pass, I am not at all I mean recently I saw in Facebook, you could transfer money and all, I know there is a feature. It is not that platform for me. It is just for time pass. And I don't put anything that is important to me or, trust wise I don't. That platform is not under my consideration. I will go to separate website, which might be even new to me, but I don't do it here"

Most people were also concerned about tracking in social media, to target ads. This impacted on trustworthiness of social media as well. Irrelevant content in the social media were also viewed as factor for reducing the trust.

Uncanny characteristic of Intelligent systems

"If social media is reading my mind from my mails, or my personal messages, I would be shocked. For instance, once I read a post, my heart did melt for a second, but later when I got back to my senses, I was absolutely shocked and the thought that google knows so much, so as to quote lines from a personal e-mail, scared me. How much of my privacy can you invade into?"

This characteristic was redundant and probably the most discussed topic in this research. Many people highlighted creepiness in the uncanny behavior of intelligent systems. This behavior might be result of system's attempt to sense user to create perfect mixed initiative. This played a primary role for users to trust or not trust the social media. Few of them tried to find a solution to such creepiness by having more control over recommendations. Having more control can enable better satisfaction (Nielsen, 1993).

"because that has more knowledge about what you are thinking. instead of that, if you have controlled recommendation, like oh I can understand how I got the recommendation, that is not creepy."

This uncanniness of intelligent systems may again be traced back to the behavior of intelligent systems. They act less intuitively, without paying much heed to the emotions of the users and concentrate more on the efficiency and finishing the tasks (Horvitz, 1999).

Boundary or leading characteristic of intelligent systems

"If I have watched a certain kind of videos(gaming) does not mean my whole front page should be filled with that suggestion. With other suggestions being minor. Also, even the searches become limited to very specific things. Feels like I am being restricted to specific things only"

It was not rare for the participants to feel that sometimes they are being restricted to certain sets of results. They showed strong resistance to the intelligent behavior of the systems, where the system presents the posts or topics based on what it thinks the user would like. The concern here is not really about the intelligent behavior, rather the lack of characteristic of intuitively understanding the user.

Factors that influence satisfaction

Two subthemes expressed the common concern of satisfaction. Hence, these subthemes were categorized under the factors that influence satisfaction. These subthemes includes implications due to control and autonomy and several other factors which influence satisfaction.

Implications due to the control and autonomy

"Wanna make improvements, let me categorize the feeds I follow. Let ME make changes, do not make changes for me. Thank you"

One of the reasons to feel satisfied in the social media experience is the factor of having enough control over the content they see and share. The tendency of the intelligent system to make decision on behalf of the user is often seen as factor of frustration. Another concern was about the ranking system in the social media news feeds. The popular items are usually ranked higher and this impacts the posts the user anticipate to see. Users prefer the intelligent system not to hide or obstruct their expectation in the name of ranking. This behavior has impact on small businesses in social media, who struggle hard to keep their presence.

Other factors that influence satisfaction

Apart from the fact that people see the aesthetic pleasure and usability as important factors to choose social media, or prefer a certain social media, the implications of adaptive intelligent systems plays important role as well.

“For me, it's mostly a way to keep in touch with family members who may not have the computer skills to use anything more sophisticated. The interface does suck, but it sucks less than buying stamps and sending paper mail, which is the alternative”

User prefers social media to be adaptive enough to understand what to show and what not show based on the usage. Factors such as asking repeated feedback, showing posts which are not user’s preference, acting by retaining the probabilistic behavior of the intelligent systems (Charniak, 1993) are often frustrating and irritating to the users.

Discussion

The results demonstrate that the behavior of intelligent system plays greater role in ensuring the satisfaction and keeping or even enhancing the trust factor. Some of the important findings of research are as follows.

Firstly, many participants pointed out, there is a restrictive feeling that users perceive while using social media. They even felt that the information was being forced upon them, and it has certain boundary. This can be compared to echo-chamber in media. (Jamieson & Cappella, 2008).

“Echo chamber is a situation in which information, ideas or beliefs are amplified or reinforced by transmission and repetition inside an "enclosed" system, where different or competing views are censored, disallowed, or otherwise underrepresented”

This behavior can be traced back to the probabilistic nature (Charniak, 1993) of the intelligent systems. The algorithm ranks the popular content and most accessed content, rather than perceiving the user's current interest and mood. To demonstrate this, let us take an example of searching "Big Bang Theory" in the google search engine. I have been an avid user of google, and google should very well know that I am a frequent reader of science articles. Hence, I expected to get some good results on articles related to science. However, all the results I got was related to the sitcom- "The Big Bang Theory". It is not just Google, but most other search engines such as Yahoo and Bing behave the same. This is due to the ranking nature of the intelligent systems, where it automatically assumed, just like many users, I am interested in the sitcom as well. This concern was shared by many participants during the research.

Secondly, the discussion on the uncanny nature of the intelligent systems. These systems are so bent upon studying the users, they often undermine the fact that, there are emotions and moods associated with the users as well (Minsky, 2006; Haugeland, 1997). To create a perfect partnership between the system and the user, a factor of understanding needs to be thoroughly explored. This also has greater impact on the trust of the users. The reason why they still continue to use the systems despite this behavior is lack of alternatives and peer pressure. Since most of the social media are built upon capitalizing the users, they tend to undermine the trust and satisfaction factors associated between the user and the system.

Finally, users do anticipate the intelligent system to work on their behalf, but they want the systems to intuitively understand the user. Intuition is a very vague term, but this word was used very frequently by participants. By intuition, they meant the ability to sense the users based on their, interests, needs and moods. We are humans and are creatures of emotions. People easily perceive the mechanical or robotic nature of the intelligent systems, which seems very mysterious to them if not frustrating or irritating. There is no strong resistance to intelligence, many participants even praised the intelligence of systems, but users like to remain in control. This is again based on the situation and moods of the users. The partnership should be in such a way that intelligent systems should sense when to give control and when to act on the user's behalf.

The research is fairly generalizable to wider population. The study involved both the participants who were not aware of presence of intelligent systems and participants who were aware of its presence. This was determined through the comments they made about the intelligent systems as mysterious code or representation of these systems as abstract character. This bias is further neutralized by having larger samples from all over the globe, which covered the maximum variability. This validity point is not just by numbers, but can be verified with the rich set of data that was used in the research (Maxwell, 2013). The data analysis involved reading and understanding hundreds of unique comments in the discussion groups, transcription of data from focus group interviews and rich data available from the online focus group. Multiple data sources also ensured the triangulation of data, eliminating certain degree of validity threats. The themes and implications are presented in such a way that, if a researcher or even a firm want to create or improve a social media website, it can act as guidelines.

However, there are some limitations associated with this research,

1. The focus group of the study involved engineers and computer scientists, who are well aware of the existence of the intelligence systems. However, this bias was taken care of, by triangulating with other data sources. The identity of the users from the other data source was unknown as well.

2. The study focused mostly on the satisfaction and trust part of usability, which could be extended to user experience. However, user experience design involves much more topics than just trust and satisfaction, which was not discussed in this research.

Conclusion

Before conducting the research, since I am interested in the Artificial Intelligence and Intelligent systems field, my belief was strong towards the use of Intelligent systems in social media. No doubt it has revolutionized the way of interaction in internet and beyond (Harper, 2015). The systems have even evolved to understand the human emotions, psychology, and behavior to take decisions and interact with the humans (Minsky, 2006; Haugeland, 1997). This paper attempts to understand how the behavior of the intelligent systems impact on the trust and satisfaction perceived by the users of social media. However, there are certain implications that are associated with the behavior of intelligent systems. For many users, an ideal social media site would carefully understand the user, know the user well enough to act on behalf of user, and act as a partner to the user without putting privacy and trust into jeopardy. This can be accomplished by giving enough control to the user and by concentrating more on the intuitive behavior of the intelligent systems.

Future work is needed to explore the reason for uncanny behavior and boundary characteristic of the intelligent system since this is a strong result of intelligent systems design. This can help to identify the gap between the implementation and Human-Intelligent system interaction. More work is needed as to find out how user experience as a whole can be improved. Other facets of usability (Learnability, Efficiency, Memorability, and Errors) can also impact the usage of social media from the perspective of intelligent systems.

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Appendix A

The focus group interview questionnaire

1. On what occasions do you use social media, which ones and how often? For example, you may use it to read news feed, or browse postings, watch videos of interest or anything else? Explain.

   Probe: How come these aforementioned social media websites? How come not others?

2. Now imagine that you are browsing Facebook (or other social media depending upon the survey responses) and encounter a specific type of post you have been frequently seeing on your page, and this was not something you expect as a part of your newsfeed (Such as frequent post about different types of Tigers that exist in India)

   a. What would you feel about this specific scenario, how often does it happen to you? How come do you think that ended up on your wall?

      Probe: Remember these post need not be entirely unfamiliar to you, you might be aware of such posts, but wasn't really expecting them to show up frequently.

   b. How tiring or frustrating are these posts? How come do you think it is tiring or frustrating?

      Probe: What would you do to stop these kinds of posts appearing again?

3. Now, imagine a scenario where you have decided to stop seeing certain kind of posts on your wall. For example, posts on the Soccer updates from the English Premier League.

   a. What would you do to achieve this goal? How strongly do you trust this would work?

      Probe: How come this is something you rarely do to stop posting? How come you do not trust this is worth your time? (This might change depending on the reply)

4. Now, imagine a scenario where you see certain post, which you did not expect to appear on your wall, but only this time, it was something you really wanted to see. For example, you are not a fan of Leonardo DiCaprio, so you never followed posts related to him. But all of a sudden you see posts related to his Oscar and you think, I wanted to see this post.
    a. What would you feel about this scenario, how often does it happen to you? How come do you think that ended up on your wall?
    b. Probe: How come do you feel satisfied or unsatisfied due to these instances? Explain.
    c. What is your take on this behavior, where you did not really ask for it to show certain posts, but knowing that you would like it, it showed anyways?
    d. What is your take on the trust, when social media behaves in such a way?
    e. Probe: How come do you still continue to use the website despite such unusual behavior?
5. Is there anything else we haven't discussed yet that you think is important related to this topic? Explain.

Pre-interview Questionnaire

Survey for research

Questionnaire for pre-interview

1. **Are you a user of social media (Such as Facebook, Twitter, Pinterest, Instagram, YouTube etc.)?**
   Mark only one oval.
   - Yes
   - No

2. **If yes for the above how often do you use it?**
   Mark only one oval.
   - Daily
   - Weekly
   - Monthly
   - Yearly

3. **If you picked "Daily", how many hours do you spend on such websites? This need not be continuous, but estimate of total usage per day.**
   Mark only one oval.
   - 1 - 2 hours
   - 2 - 4 hours
   - 4 - 6 hours
   - My life is virtual (> 8 hours)

4. **Out of the Social media you use, please indicate the social media you use the "most" and "least".**

Figure 3. Pre-interview survey questionnaire

Appendix B

Reflection

I am an avid social media user. The origin of this paper started with finding current issues with the social media experience. My research interest lies in improving collaboration between the humans and intelligent technologies. Web technologies are changing drastically over the years, and intelligent system plays important role in it. Based on my experience with social media, I was curious about what other people think about social media experience, especially satisfaction, and trust implications. But finding a suitable way to capture useful data proved difficult. I pondered on ways of collecting data, which is rich and valuable for my research. At first, I thought of using diary study as a method for data collection. At that point, I had not thought about data triangulation. When I discussed this with my instructor, she asked me some invaluable questions. This made me realize that diary study might not be useful to capture the data. Because, the chances that user encounter an interesting scenario on daily basis was too low, or so I thought. Also, I was not sure if this method could capture the data I wanted.

Next, I thought about interviews, since people's take on trust and satisfaction is individualistic. But such trust encounters while using social media is heavily dependent on user's memory. I realized that just by conducting interviews, I won't be able to capture all the aspects of social media experience. During my discussions on the project with my peers, they seemed to think interviews as proper method for my research. I studied different papers, which involved capturing data based on rare encounters, and focus group seemed like a perfect method. I was still bothered about the problems focus group would pose since I won't be able to capture individual's take on satisfaction and trust. But, the tradeoff was great. The brainstorming behavior of focus group can trigger various topics and individuals are entitled to give their own opinion. I laid some ground rules to ensure the discussion went smoothly. Participants were not aware of focus group discussions, so I explained the rules of focus group. At times, some people were dominating the discussions, but I made sure to neutralize this by asking opinion from less active individuals as well.

Still, I was not convinced with just relying on this method alone; I thought about various ways of capturing such data, and in the class, my peer talked about online focus group. This seemed like a wonderful idea, and I saw great advantage in this method. In online focus groups, people are not bound regionally and this helped in generalization as well. I looked for various focus group websites and found a suitable one, which had a technique to reduce bias. There was a choice for people to comment first and see peers' comment after answering. Finally, from the discussion with my instructor, I identified my final data source; discussion in the existing online forums. This was daunting, since finding a credible forum which do not force people to comment was a hard task.

Soon, rich source of data overwhelmed me. There were about 664 unique comments from the online forums. The length ranged between two sentences to fifteen sentences. Apart from this, I had data from 12 participants in the online focus group and transcription from the tradition focus group. The problem now was analysis of such rich set of data. I studied again to find out, how people handle such data and I found that researchers usually code from the three data sets separately. Then, they identify subthemes, finally categorizing and collating everything to major themes. This seemed like a plausible way of analyzing data and followed similar steps.

Coding thousands of lines of data proved hard. I used affinity diagramming method to clearly classify all the codes into major themes. I found very interesting themes from the analysis. Some were anticipated and some came by as a surprise. I went back to literature to find some explanation for some of the themes.

Writing a research paper, was very difficult. I had so much information, but how to communicate to readers? How to make readers match their conceptual model with my mental model? I prepared a draft which displayed the implications of my research, but draft review feedback from my advisor indicated I was not entirely successful in communicating the implications properly. I had made some confusing arguments in the literature review section and some unconvincing statements in methods and results. I went through each feedback carefully to address each of those issues. I saw why my feedback providers felt difficulty in understanding the implications. I had not weaved everything together properly, there was no interrelation between the results and implication, or at least it was weak. Feedback from my peers also helped greatly in revising poor version of my draft. I did multiple proofreads to ensure, the reading is fluid and transitions were in place.

This was a very exciting experience for me, it was daunting but I immensely enjoyed each and every bit of it. I learned a lot of things about qualitative research methods. To summarize, I learned how to decide on topics, data collection methods, how to arrive at theoretical frameworks, how to analyze the collected data, generalizability, credibility and validity implications and finally communicating my idea to the readers which matters the most. I will remember these important takeaways for years to come. This project has forever changed my viewpoint on qualitative research methods, which is of positive and curious nature.