People, Technologies, and Organizations Interactions in a Social Commerce Era

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Abstract. Social commerce, in today's era is the wealthiest combination of customer oriented technologies and latest commercial features. It has a direct impact on the E-commerce, generating large amount of benefits. It understands both technical and social framework to fulfil the customer's requirements on social media websites. In general, E-Commerce is more beneficial at social commerce. Our results show that customers are more satisfied by the ease of usefulness, thereby enhancing their wish to purchase and trust. For engineers and designers, our results describe the importance of social media commerce in today's era for constructing users trust on social media commerce sites and supporting their wish to buy the trending products.

Keywords: Socio technology · Customer oriented · E-commerce · Social commerce

1 Introduction

In media new technologies are giving a serious impact on the society. Households are flushed with these types of changes. Social interactions in the household have been increased by the passage of time. This indeed has increased interactions among the family members leading several conflicts between them. The generation gap has reduced digitally, giving rise to healthy relations, whereas, has led to the privatization within the family. For the same reason, I seek out to investigate the research "How Social Media is giving a severe impact on the social interactions within the households?"

In today's era of E-Commerce (Electronic Commerce) through booming entrepreneurs, we can see a great impact in the online retailer. In this the users buy, do searches, connect with the friend lists are sometimes simply search for the desired products or services. Our aim is to understand E-commerce from the very beginning stage to the factors which various countries supported for internet penetration. ITC's made a new form of commerce known as social commerce which will be analysed in this paper. The purpose is to show that Web 2.0 technology and Social Media have made different ways to communicate, collaborate and share information to a large number of people who are associated with this virtual relationship. The consumer now becomes the social consumer which shares the same passion and taste with other consumers using different social media handles. It not only constraints the buyer of the

A. P. Pandian et al. (Eds.): ICCBI 2018, LNDECT 31, pp. 836–849, 2020.
https://doi.org/10.1007/978-3-030-24643-3_98

product, but helps to increase his/her reach to explore new products or to a 'place' where a consumer can connect with people on the same frequency.

The statistics say, Facebook's monthly active users have increased by 23% from 901 million in March 2012 to 1.11 Billion in March 2013. This increase leads to increase in the number of active mobile users from 488 million to 751 million by March 2013, which represents a 54% hike from the last year. Same is with Google Plus; this is the second largest social media network which grew its monthly active mobile users by 33% in the same year. Similarly, Twitter just like Facebook has set up its users to 44% in the same year.

Predicted Business with s-commerce strategies are in need to consider the mobile device usage in order to fulfil the customer needs while keeping the customer loyalty and trust high, which adds up to one of the important factors for success of online commercial activities. Same is with the m-commerce field in which they need a high social media network to shoot their business up. New mobile social commerce design framework must be completely flexible and should have reliable guidelines which must be accepted by each and every concept of social media business platforms. Formal definition of s-commerce is different from any other type of commerce as all of the commercial transactions depend upon the type of Web Infrastructure and participation of users.

S-commerce linked with Web 2.0 support online transactions and user contribution to help in the acquisition of products and services. The unique infrastructure that a social media handle provides, allows its users to generate data over time.

Say for example, Facebook, Google plus and Twitter are the social media service providers which give their users a specific domain to generate data with the help of Web 2.0 technologies. They are also the example which made social media providers to gain importance in the internet over the years which is a blessing from social commerce.

2 Literature Survey

Recently, social media rapidly changed in brand management and understanding this change is now critical which affected brand management. The paper focuses on existing system and introducing a framework of social networks which impact on brand management. System brands are first for consumers and are to be used in living their own lives [McCracken 1986] and today's challenge is to understand the deep sources and dynamic nature of brands meaning. Author proposed meaning transformation McCracken's model to understand the various brand's meaning. They have presented 20 years of Consumer Research Addressing on Socio cultural, Experiential, Symbolic and Ideological Aspects of Consumption and present Consumer Culture Theory (CCT) which is used for understanding consumption and marketplace values of products. They have discovered three misconceptions about the nature and the orientations of CCT [1].

E-commerce is the evolved form adoption of Web 2.0 technology and its capabilities to understand customer participation and achieve greater economic value in the market. These phenomena are referred as social commerce. Research on the social commerce techniques were done, reviewed and E-Commerce and Web 2.0 techniques were presented. For this, they have used Facebook, Amazon and Starbucks websites.

Social commerce is referring to social, creative and collaborative approach for online marketplaces. The figure shows the author proposed model. The social Commerce model includes phases, namely Commerce, Community, Conversation and Individuals. In conversation phase, we find out the interaction among the users of social media. Fundamental requirements of conversations are Communication, Communities and Connections. Functions of communication are to provide a communication channel between users on the social media. Communities are related to the aggregation of participating groups. The limitations of these papers are identification Web 2.0 and E-Commerce design characteristics [2].

New techniques to recommend friends with similar location preference, location based social network (LBSN) - users, in which friend's online friendship information and the offline user behavior are taken into account. The proposed approach includes Markov chain, cosine similarity based on location clustering and threshold evaluation. In this paper, the authors have focused on relationship perspective to observe the relationship between users of a social network site. Here they describe the buyers and the seller relationship and their roles. It also describes the role of the internet and interfaces. Data is collected from suggested information sources, including suppliers. Suppliers and salespeople are more important than the internet. It directly affects IT adoption.

When we make use of the website for search PEOU, it affects IT adoption because the required information is embedded in the IT. In this the web development is also introduced. In this, firstly, a survey is conducted comparing consumers in China with their U.S. counterparts, and it is shown that a cultural perspective is pertinent and valuable. A recent social media change rapidly. In this, there are social media groups of internet applications that build new technology, that are used to exchange user generated content. A model has been proposed and is the extension of the planned behavior. The author has discussed about the managerial implications [3].

In recent years, social commerce has been a new technology, in which seller and buyer connect to each other using social network. Social Commerce and Social Shopping are the forms of Internet-based which are called as "Social Media" and this allows people to participate in marketing and for selling the products online and provide services in online marketplaces. Applications are needed to merge the Online Shopping and Social Networking into each other. The difference between Social Shopping & Social Commerce is that Social Shopping is connected to the customers and Social Commerce is connected to the sellers. Social Shopping is spreading around the online world. Online user's reviews are important to collect source of information for substituting, consumers, complementing and it's important for understanding customer's requirements. During this investigation has been done to understand Enterprise social networks and to develop models that understands the social psychological processes [4].

The study examines three commonly-used interventions to understand how they influence different user's beliefs and subsequent participation. This tested model has data collected from 366 members. It provides the validated theoretical model that improves the socio-psychological processes governing employees. It also contributes to a more detailed understanding of how and why corporate staffs participate in social networks. It also demonstrates the three commonly used management interventions - Sellers facing challenges of customer related marketing, planning to fulfil the customer requirements and finally building the customer product. In this they have proposed integrated model to describe the components. Structural Equation Modelling with the Partial Least Squares (PLS) is used to analyze valid data of customers. Results show its effect on SC consumer value. This data is collected from Facebook. Results show the benefits of social interaction [5].

In this [6] they propose Collaborative Filtering techniques for the top-n recommendation task they used bi-clustering neighborhood approach. The result shows that the proposed techniques generates a better recommendation that the existing State-of-Art algorithm on sparse data. The performance of the Bicluster Neighborhood (BCN) Framework is evaluated on five real world dataset such as Paypal dataset, lastfm dataset, lastfm friends dataset, and delic bookmarkdatset. Performance of BCN techniques is compared with the three different algorithms, namely SLIM (Sparse Linear methods), Item CF (Collaborative Filtering), and WRMF (Weighted Regulation Matrix Factorization).

They proposed Probabilistic techniques to resolve Diversity-Accuracy Dilemma in the RS (Recommendation System). This proposed recommendation system has two models: First one is that maximization of the accuracy and second one is specified of the recommendation list to the tastes of the users. A recommended technique is based on the Markov model. For this experiment they are using two real datasets such as Movielens and Netflix. These datasets divided into the testing dataset and training dataset [7].

They proposed Topology-based ensemble model for combining users own taste and his trusted users/friends testes. Experimental analysis performed on the Flixster, Epinions, and Ciao for the better results. A proposed technique is not only applicable for Model-Based ensemble, but also Instance-Based ensemble recommendation techniques. Sentiment latent topic model (SLTM) is used for build a connection between sentiments and words [8].

In this [9] they propose emotional aware recommendation approach to incorporate an emotional context into music recommendation. They are using Chinese twitter services dataset. The performance of this technique improved in terms of precision, recall, hit rate and F1 score. A proposed technique is compared with two existing techniques such as Fine grain emotion from micro blogs and Coarse-Gained emotion information. In this they firstly music service is connected to the microblogs services such as Sina Weibo and Twitter for exacting more listing records. In this they improve the accuracy and efficiency of music recommendation techniques.

They proposed techniques for providing personalized service recommendation to individuals user, for this they used trust relationship between services and users. A proposed recommendation technique is based on the collaborative filtering approach such as trust-based service recommendation. TSR techniques are compared with other five approaches relation based TSR, QoS on response rate, QoS on trough output, HITS and PAGERANK [10].

In this [11] they propose techniques for the solving the large scale matrix factorization problems in recommendation system. In this they used optimization techniques such as cyclic coordinate decent approach (CCD) and it is applicable to the large scale problems such as Maximum Entropy Model, NMF problems, Sparse Inverse Covariance Estimation and linear SVM. CCD approach updates the single variable at a time while keeping other fixed. The proposed system is comparing with the ALS, SGD, and CCD++ in large scale data. The dataset used for the experiment is Movielens 10 m, Movielens 1 m, Yahoo Music and Netflix.

They propose improved matrix factorization approach such as Bounded matrix factorization (BMF) approach for rating matrix. They test performance of the proposed algorithm on the real-world dataset such as Netflix and compare state-of-art algorithm with SVD++, SGD, Bias-SVD and ALSWR [12].

3 Research Methology

In recent years, the trend of web service on the Internet is increasing. There is a need for great effect service recommendation organization. Existing methods mainly focus on the characteristics of individual web services (e.g., functional & Non-functional characteristics), they ignore the user's point of view on the service, so they cannot provide a personalized service recommendation. In this paper, network modelling is used to study the relationship of trust between users and web services analytical technology. Based on our knowledge and service network model, we have proposed a collaborative research.

A filtering algorithm called Trust-Based Service Recommendation (TSR) provides recommendations for personalized service. This systematic approach for modelling and analyzing service networks can also be used to recommend other services for the study [6].

The trust region is a term used in mathematical optimization to represent a subset of the region of the objective function approximated using a model function (often quadratic function). If an appropriate model of the objective function is found in the trust region, the region is expanded and conversely, when the approximation is bad the region contracts. Trust region methods are also called restricted step methods.

In Computer Science, clique problem is a computational problem of finding a clique (a subset of vertices, also called a complete sub graph adjacent to one another) graphically. It has several different formulas, depending on what clique and information about that clique should be found. Common formulas for the clique problem include finding the maximum clique (a clique with as many vertices as possible), finding the largest clique in the weighted graph, enumerating all the maximum cliques (in expandable cliques) and solving the decision problem test whether the graph contains larger cliques than the given size.

The problem of clique occurs in the following real-world situation - Consider a social network where the vertices of the graph represent people and the edges of the graphs represent mutual acquaintances. Clique represents a subset of people who know each other and algorithms to find Clique can be used to discover groups of these mutual friends. Clique problem has many applications in Bioinformatics and computational chemistry as well as in social networks.

The first version of the clique problem is difficult. Clique decision problem is NP complete (one of Karp's NP complete problems). The problem of finding the maximum clique is hard to deal with and difficult to approximate with fixed parameters. This is because there is a graph with many maximum cliques exponentially, and we may need an exponential time to list all the maximum cliques. Therefore, much of the theory about the clique problem is focused on identifying special types of graphs that allow more efficient algorithms, or establishing computational difficulties for common problems in various computational models.

The reviews and ratings are taken from students of Bharati Vidyapeeth for testing purpose and around 300 students have participated. The proposed system was provided to them and they were asked to do shopping on the website. They then provided their valuable feedback. The size of the feedback data file is 100.9 KB with 300 records in it.

4 System Architecture

Proposed system architecture is shown below which includes review and rating of websites of the products, recommendation of product and websites as whole to be used, forum and comments of products and five types of websites.

The paper mainly focuses on how online shopping via the website and recommendation affect trust of customers with attitudes. Consumers are the main actor of the marketplace. The role of consumers in the marketplace is to consume and purchase products and services in the market. The difference between the buyer and consumers is that, that the buyers are people whose role are industrial, ultimate and intentional purchasers.

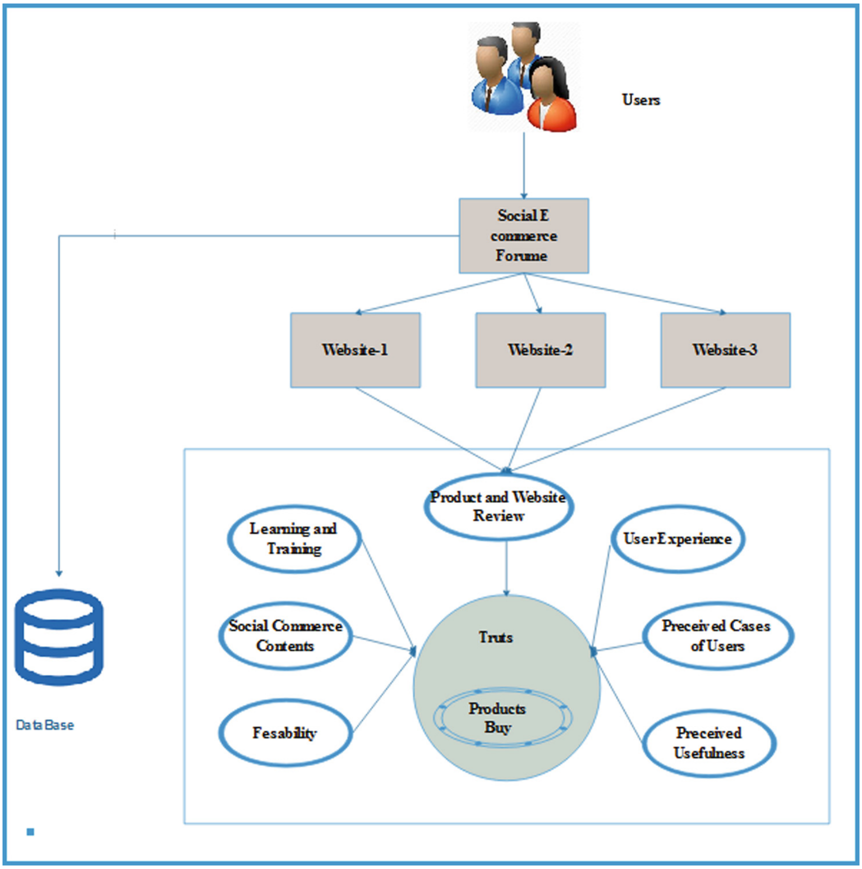

Fig. 1. System architecture

Problem recognition, information search, evaluation, purchase decision, post purchase behavior. Social media strategy below flow chart shows that the social media flow decision making phase. In this several factors are affecting on that the as internal factors and external factors which are leads to social media. External factors are considering popularity and fast growth and it provide low cost solutions for social media. In which phases are including namely external factors, internal factors, activates of social media, expected outcomes, other factors of social media. New farms are going on social media whose follow up same activities of social media which are communication with user of media, announcing of new products these activities are according to the offline marketing (Fig. 1).

5 Mathematical Model

Let S be a solution of problem

S = {I, P, O, Sc, Fc}

Where,

I = Input of System

O = Output of System

P = Process in the System

Sc = Success case of output of system

Fc = Failure case of output of system

• Process:

1. P1 *//Social E-Commerce Forum*

Login to the websites and surf on shopping websites for product that user wants to buy, search the product. The search products and user session details are taken for further use.

2. P2 = {P1}; *//Forum and community page*

Login to the social forum and surf for subjects that are trending and add comments if user wants them.

Subject is "Website User Experience".

One of the most frustrating experiences for users of the web is waiting for a page to load for long. With the rise of the mobile devices people are accessing content all over the world or many different platforms.

Comments:

Comment1: I am familiar with these kind of bad user experience so, it very frosting for me to find. Is anyone having better user experience website to do surfing?

Comment 2: Yes, I recommend krusha website for searching and it is very useful and easy to use. They provide good user experience. I am using these websites from last year and I bayed many delicious pastries and they delivered stuff with quality, so it is very trustful website we use NLP concept sentiment analysis in which every comment is check for positive and negative words to identify negative user and positive user.

3. P3 = {P2}; *//Recommendation and rating page*

Then in recommendation page search every website page for user query and find it by TF-IDF algorithm.

I. Term Frequency (TF):

$$ft = \pm + \log(I + tf_{i,d}) \tag{1}$$

Where,

$tf_{i,d}$ is log terms frequency of terms t in documents d

II. Inverse Documents Frequency(Idf):

Where,

N is the total no of documents in collection so, from Eq. 1 and Eq. 2 is

$$W_{t,d} = \left(1 + log1 + tf_{i,d}\right) log_{10} \frac{N}{dft}$$

Query and location is selected for recommendation and TF = Idf recommend websites. This way every page of all websites is search for user keyword. In all pages check the probabilities of websites reviews and recommend website details to user.

4. P4 = {P3};

User Uses recommendation and visit website for shopping. After shopping it provides ratings for all factors and reviews about product and website are taken and stored them in database. Here Cronbach's alpha is used to find out intercorrelation among the 8 factors.

The standardized Cronbach's alpha can be defined as

$$\alpha_{standardized} = \frac{K\bar{r}}{(1 + (K - 1)\bar{r})} \tag{2}$$

Where K is as above and r the mean of the K (K-1)/2 non-redundant correlation coefficients.

Measures to find Internal consistency some internal consistency classes are defined with cronchbach alpha range (Table 1).

Table 1. Cronbach's alpha range table

Cronchbach's alpha	Internal consistency
$0.9 \leq \alpha$	Excellent
$0.8 \leq \alpha < 0.9$	Good
$0.7 \leq \alpha < 0.8$	Acceptable
$0.6 \leq \alpha < 0.7$	Questionable
$0.5 \leq \alpha < 0.6$	Good
$\alpha < 0.5$	Unacceptable

5. P5 = {P4}; *//Result*

To check the probabilities of every parameter, we take all the ratings of eight parameters and show in the way of mean, S.D, Variance, alpha.

Then Trust Cliques Algorithm is used to find Trust. Trust is directly affects the intention to buy.

Sc = When we find class of user, Is it positive or negative.

Fc = When it fail to identify behavior of user.

6 Algorithm

Algorithm: Trust Communities Algorithm:

Input:

Communities size n, iteration limitation l,

User set U, user trust matrix T;

Ensure:

Collection Communities;

Communities = U, n_c = | Communities|;

While, n_c = 1 or number of iteration < l do;

For i = , n_c do;

C_i = the ith Communities;

J = the set of $C_1^{`}$ s connected vertices;

$$\Delta Call_{max} = 0$$

for each $V_j \in J$ do;

$$C_1^{`} = C_i \cup V_i;$$

If $C_1^{`}$ satisfies the first condition of n-trust-clique;

Then;

Calculate ΔCol for the change;

If $\Delta Call > Call_{max}$ then

$$\Delta Call = Call_{max};$$

$$C_i = C_1^{`}$$

end if;

end if;

end if;

if $\Delta Call_{max} > 0 \vee Random(0,1) > pro$ then;

delete clique C_i to Communities;;

store current partition result Communities; and the corresponding Coll;

end if;

end if;

n_c = |Communities;|;
end while;
return optimal Communities with the maximum value of Coll;

The Trust Community Algorithm is required because of Trust is one factor on which all other factors are connected together. If trust has more value then its impact on intention to buy is always be high. This trust factor need to be calculated between users and websites so it help the users to decide from which websites products are good and with good quality. From websites company perspective it will build trust between users and website that will lead to increase in business profits.

So trust community algorithm is made in such a way that it manage to make communities that have High trust, low trust and neurals or average trust. Many users are trust their friends and relatives largely, so they formed groups. This groups are called Communities when they become large in size. The cliques also called as communities, clusters, collection or Groups. In above algorithm Coll is defined as Global Collection of users. It has following given formula:

$$Call = log\left(\frac{\sum_{ci \in Communities} Call_i}{|Communities|}\right) \tag{5}$$

So, those users get coll values similar are put into one community and this way it forms and manages big communities of users.

Process P2 is log into Social Commerce forum, to find details of products like price, vendor, company details and will know the technical aspects with price details of product. Process P3 checks reviews and ratings of product and websites. Also, on shopping website users can add their ratings and reviews on product and websites. For rating and reviews, rating is given in star format that is out of five. One star is extremely poor, two stars are bad, three stars are average, four stars are good and five stars are best.

This is the website module and includes terms - familiarity, learning and training, user experience, perceived ease of use taken from the star rating 1 to 5. 1 means strongly disagree and 5 means strongly agree. These terms are taken from user on websites in star rating and user reviews about websites and its products.

User provides valuable information or opinion about learning and training, user experience which are connected to perceived ease of use and it connects to the perceived ease of use.

Range of Familiarity: 0.455 to 0.873
Range of Learning and training: 0.682 to 0.759
Range of User Experience: 0.649 to 0.849
Range of SCC: 0.627 to 0.759
Range of PEOU: 0.659 to 0.746
Range of PU: 0.629 to 0.840
Range of Trust: 0.555 to 0.778
Reviewpage.jsp (Table 2)

Table 2. Reviewpage.jsp

Familiarity	****	4
Learning and Training	***	3
User Experience	*****	5
Social Commerce Construct	***	3
Perceived case of use	****	4
Perceived Usefulness	****	4
Trust	****	4
Intension to Buy	***	3

Reviews:

This websites has very good UI. It provides best discounts than others

This websites has Very Good UI. It has provides Best discounts than others.

Product quality is also best. Best

As we see that user reviews is positive because it has positive words which denote its positivity (Table 3).

Table 3. Word count table

Word	Weight count
Very Good	1
Best	2

This way we assign users class like positives user, negative user and neutral user, all respective user reviews which user has submitted on websites. Positive user are always has high Trust value so their intention to buy products are always high.

After that we also take a note of user search on websites user involvement on social commerce constructs (SCC) and take his/her session time to identify how much user in using SCC.

These are above range in which if values are come then it is satisfactory degree of internal consistency reliability.

Following are examples of reviews given by Users in Social community forums and website reviews are taken into consideration for internal consistency measurement which is shown in below table with factors values for reviews and comments.

Familiarity:

FA_1: I am acquainted with searching information regarding products on the internet.

FA_2: I am acquainted with purchasing products on the internet.

FA_3: I am acquainted with enquiring about product ratings on the web.

Learning and Training:

L_1: I know how to operate a computer and use the web.

L_2: I am well-educated to use the web to buy products online.

L_3: My learning and training about online shopping has been useful.

User Experiences:

UE_1: I am capable to operate a computer.

UE_2: I am capable to use the web.

UE_3: I have used the web from a very long period.

Perceived Ease of Use:

SSC_1: I always make use of portals and blogs for gaining details about a commodity.

SSC_2: I always use customer provided grades about commodities on the web.

SSC_3: I always use customer provided suggestions to buy a commodity on the web.

Social Commerce Constructs:

PE_1: It is very easy to become skilled at using the websites.

PE_2: It is very easy to learn to use the web.

PE_3: The websites that I use for shopping are flexible to interact with.

Perceived Usefulness:

PU_1: Enquiring and purchasing on the web is very useful for me.

PU_2: Enquiring and purchasing on the web makes things easier for me.

Trust:

T_1: Assurance provided by the websites used by me for my last purchase seems trustworthy.

T_2: I can count on the worthiness of the website that I used for my last purchase.

Intention to buy:

IU_1: I am ready to give the details to socio-economic retailers for better shopping experience.

IU_2: I am okay to use my card to buy from a social-commerce retailer (Table 4).

Table 4. Score table

scores:

Perceived Usefulness	Trust	Perceived_ease of_use	User Experience	Learning and Training	Social Commerce Constructs	Familiarty	Intension_to_buy
-0.267405	0.907798	-0.772342	0.797666	0.829146	0.681229	0.245207	0.1513
1.260623	0.1513	0.943973	-0.041982	0.829146	-0.035854	1.226036	0.1513
0.496609	1.664296	0.943973	0.797666	0.829146	1.398312	2.206865	0.1513
-0.267405	0.1513	-0.772342	-1.721279	-1.333843	-0.752937	-0.735622	-1.361696
-1.031419	-0.605198	-1.630499	-1.721279	0.829146	0.681229	0.245207	-0.605198
1.260623	-1.361696	0.085816	0.797666	0.10815	-0.035854	-0.735622	-0.605198
-0.267405	0.907798	1.802131	1.637314	1.550142	0.681229	-1.716451	0.1513
0.496609	-0.605198	0.085816	0.797666	0.10815	-0.752937	-0.735622	0.1513
0.496609	0.907798	0.085816	0.797666	-1.333843	-1.470021	0.245207	0.1513
-1.795433	0.1513	0.943973	-0.881631	1.550142	-1.470021	1.226036	-1.361696
-0.267405	-0.605198	0.943973	-0.881631	-0.612847	0.681229	-0.735622	-0.605198
-1.795433	-1.361696	0.085816	0.797666	-1.333843	-1.470021	-0.735622	1.664296
1.260623	0.907798	0.943973	-0.041982	-1.333843	-1.470021	0.245207	1.664296
-1.031419	0.1513	-1.630499	-0.881631	-0.612847	-0.035854	0.245207	0.1513
1.260623	-1.361696	0.085816	-0.041982	0.829146	1.398312	0.245207	0.907798
-0.267405	-1.361696	0.085816	0.797666	-0.612847	1.398312	-1.716451	-0.605198
1.260623	1.664296	0.943973	-0.041982	0.829146	0.681229	0.245207	1.664296
0.496609	-0.605198	-0.772342	-0.041982	-1.333843	-0.035854	1.226036	-1.361696
-0.267405	0.907798	-1.630499	-1.721279	0.10815	-0.752937	-0.735622	0.907798
-1.031419	-0.605198	-0.772342	0.797666	0.10815	0.681229	0.245207	-1.361696

7 Conclusion

Social network is used increasingly, because of this e-commerce is impacted on social network site. Our findings and results show how increases in purchases intend towards social commerce. From this system results, we can get consumers profiles who buy products online. Results show that Social Commerce Constructs, Communities, Rating and Review of products lead to trust. Trust is established from the Social Commerce Constructs it affects consumer's intentions of buying products. Trust community Algorithm plays major role for focusing on positive users to provide them more positive experience and negative user will get importance because they shows limitations and less quality.

Acknowledgements. The authors are grateful to acknowledge the support of faculty and research scholars of BVDU, COE, PUNE who spent their crucial time while conducting this survey and participated in filled the questionnaire to provide their intellectual feedback related to Social commerce era.

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