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Loyalty and Brand Related Customer Behavior Analysis on e-commerce Platform Using Transfer Learning

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ABSTRACT: Branding is supposed to be an influential tool for building enduring associations between brand users and company. Committed users of a particular brand are likely to make repeat purchases, share positive information, and pay premium price for their favorite brands. Nowadays, social media tools facilitate members of brand communities to connect globally in order to share and distribute information about their favorite brand through various social networking sites. The primary aim of the marketing goal is to achieve customer loyalty, but building loyalty and reaping its rewards remain ongoing challenges. Theory suggests that loyalty comprises attitudes and purchase behaviors that benefit one seller over competitors. Yet researchers examining loyalty adopt widely varying conceptual and operational approaches. The purpose of this study is to examine brand behavior from popular e-commerce websites. This study investigates effects of brand community in the social media on the customer-centric model (customer relationship with product, brand, company and other customers) and its impact on brand affect, brand trust, and brand loyalty. The research method uses the invariant cross-domain transfer learning (ICDTL) techniques to examine the relationship between customer loyalty and brand behavior. The experimental analysis showed that the loyalty of both female and males are highly depends on product features and brand names for three major categories such as home applications, fashions and electronics.

Keywords: Branding, Brand Trust, Customer Loyalty, Social Media, Transfer Learning techniques.

I. INTRODUCTION

In today's competitive market with the increasing complexity of the media, brand creating has become more important and challenging. The development of marketing, and expanding studies on consumer behavior field, increase the importance of the relationship between brand, identity and culture [1]. According to [2], the relationship between consumer and enterprise is one of the crucial factors in relationship marketing. Brand community is a concept that creates a new way of making relationship between consumers and an especial brand, and not only is about the relationships between consumers and companies, but also is about the relationships between consumers with each other. It seems that applying brand communities is an effective approach to build and maintain such consumer-brand relationships [3]. Also, with emergence of internet, automatic creation of brand communities that are geographically unbounded has become possible [4]. Virtual brand communities are a powerful tool for marketing, because these communities help to understand the consumer needs, interests, behaviors and concerns, also they help to promote consumer involvement and brand loyalty [5]. Therefore, marketers must recognize the virtual brand communities as a tool to build consumer-brand relationships, and should become interested in managing their online communities in the internet [6]. On the other hand, the emergence of social media networks has revolutionized marketing practices and led to a shift to "user-driven technologies" [7]. Some of the most well-known social media networks include Twitter, Facebook and YouTube. The popularity of social networks such as Twitter emphasizes the changes in media consumption [8].

Many brands have taken to social media networks to connect with consumers, by using them to create valuable relationships before, during and most importantly after purchase. Careful adoption of social media marketing

(SMM) techniques can help to reinforce and increase brand awareness amongst consumers, as consumers spend ever-increasing amounts of time on social networks. Social media allows brands to discover exactly what customers are interested in and then use this information to upgrade their products and services in order to meet those needs [9,10]. This can be accomplished by targeting advertisements based on potential customers' profiles, as businesses can collect information such as age, demographics, interests, hobbies, music etc. - they can then advertise certain products and services only to specific people who meet the required criteria. Social media is therefore a more efficient use of marketing costs [11], which is important for even small and medium sized enterprises (SMEs) as they are expected to have far smaller budgets than the larger companies. Moreover, firms use social media not just to find new customers but also to maintain and retain their existing customers. There are several existing academic works about customer relationship management (CRM) strategies and user engagement [12,13]. However, there exists no previous study examining the various reasons of why individuals communicate with the brands through social networking websites. Individuals have been rapidly increasing their daily use of the Internet by engaging on social networks. Still, there is a lack of academic study about user-brand loyalty through social media. The following research aims to fill these gaps and investigate the user-brand relationship through social media and the impact of social networking websites on customer loyalty. The ICDTL techniques identified the brand behavior with customer loyalty by training the common features based on its entropy basis. The sampling learning vector gradient (SLVG) is used to minimize loss on the training data and also related to the fast weights or slow weights of the trained features. Finally, the output of the deep neural network is used to estimate the loyalty of the user on brands.

The remaining paper consists of: Section 2 describes the survey of recent techniques, which was used to estimate the customer loyalty and brand affects. The explanation of the proposed method is represented in Section 3. The validation of the ICDTL techniques against several traditional neural networks using e-commerce websites data are presented in Section 4. Finally, the conclusion of the paper with future development is depicted in Section 5.

II. LITERATURE REVIEW

In this section, the survey of recent techniques are discussed, which are used to identify the customer loyalty with brand. The advantage of the existing techniques are also described with its limitations.

T. M. Nisar, and C. Whitehead, [14] investigated the relationships between customer satisfaction and brands, which was used to identify and maintain the loyalty of user through networking sites. The method collected the strong evidence that majority of social users follows the brand pages through websites. The difference between user's attitudinal and behavioral loyalty were identified by this method. Finally, the information obtained about brands showed the user's level of trust through social media web pages. The social media were used by firms to find a new customers and also to maintain their existing customers. Therefore, customer engagement cycles were used to identify the individual and brand interactions. However, the most influencing factors that affects the customer loyalty is trust and these generalized findings may become irrelevant in the future development.

G. F. Watson,*et al.*, [15] examined the heterogeneity consequences by mapping conceptual approaches using an item-level coding of extant loyalty research. Then, the performance process of strategy and loyalty were moderated by testing the operational and study-specific characteristics. The results clarified the dissimilarities in loyalty building strategies, conceptual approaches using an item-level coding of extant loyalty research and finally, how the loyalty differentially affects performance and word of mouth. Although loyalty was primarily conceptualized as the alignment of attitudes and behaviors, items used to measure loyalty often. But, this study had limitations such as the construction and the limits were limited to variables for which there exist enough data for analysis. This framework was a summary of important loyalty-related constructs, not an exhaustive list.

B. Godey,*et al.*, [16] investigated the relationships by analyzing pioneering brands in the luxury sector (Burberry, Dior, Gucci, Hermes, and Louis Vuitton). The study developed the structural equation model for addressing the gaps in prior social media branding according to review of 845 luxury brand consumers from Indian, French, Italian

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and Chinese. Specifically, the study demonstrated the links between social media marketing efforts and their consequences (brand preference, price premium, and loyalty). The study measured brands' social media marketing efforts as a holistic concept that incorporated five aspects (entertainment, interaction, trendiness, customization, and word of mouth). Another contribution of the study was to find social media marketing efforts (SMMEs), which have a significant positive effect on brand equity and on the two main dimensions of brand equity: brand awareness and brand image. But, the main limitation of this study was its generalizability beyond the luxury sector. While the results were likely to be useful in the luxury sector, they may not be directly applicable to other industries.

X. Zheng, *et al.*, [17] explored the concept of user engagement in the context of online brand communities. A research model was proposed to explain how brand loyalty was developed through user engagement. The research model was empirically tested with an online survey study of 185 current Facebook members. The experimental results revealed that user engagement influenced brand loyalty both directly and indirectly through online community commitment. This paper enriches knowledge of people in the area of brand engagement by presenting a research model that introduced the concept of user engagement in social media research and empirically examined its role in building brand loyalty in online brand communities. But, the current study was subject to some limitations. First, the selection of respondents was bound to the Hong Kong area, while Facebook members were distributed globally. Second, this study has not taken the actual purchase and word-of-mouth behavior into consideration.

S. Kamboj, and Z. Rahman, [18] examined the concept of member’s participation in the context of social media-based brand communities. A research model was developed to describe how brand loyalty was influenced through member’s participation. The research model was tested empirically with an online survey of 436 members of any of Facebook fan pages of Indian hotels. Results also indicated that perceived benefits and costs lead to enhance the members’ active participation in community. Age did not moderate this effect; younger and older members were equally influenced by the perceived benefits and costs. However, this research was subject to a number of limitations: First, the respondents were selected from India, while Facebook users are located globally. This study considered only brand commitment and brand loyalty as outcomes of community participation. In addition to these, other constructs, for example, purchase intention, word-of mouth, actual purchase behaviors, and brand equity were not utilized to confirm the findings of using social networking sites.

M. W. Nyadzayo, and S.Khajehzadeh, [19] investigated the mediating role of Customer Relationship Management (CRM) quality to better explain the effects of service evaluation variables (service quality, customer satisfaction and customer value) on customer loyalty. The study also investigated the moderating effect of brand image on these mediated relationships. The mediating role of CRM quality on the relationship between the service evaluation variables and customer loyalty was supported. Further, it was found that the indirect effect of customer satisfaction on customer loyalty through CRM quality was stronger when perceived brand image was high than when it was low. The results have implications for relationship managers, brand managers and scholars who use service evaluation and relational metrics to predict customer loyalty. This study has some limitations: First, while the results may be generalizable to other countries, the economic, geographical and cultural make-up of South Africa should not be overlooked when interpreting the results. This was due to the differences in macro market conditions and micro consumption behavior between the two markets. Second, the CRM method used data from a business-to-consumer relationship within a single industry, suggesting the results cannot be immediately applied to other industries and/or to business-to-business contexts.

III. PROPOSED METHODOLOGY

Today managers are facing the challenge of establishing and continuing relationships with their customers. It is even tough because customers have a wide range of choices and more access to information. The different activities of the firms including price discount and strong marketing strategies make this task even more difficult. Because, customers play an important role for corporate business sustainability. Every company is trying to obtain higher customer lifetime value, by preparing a variety of marketing strategies, but this time, the focus and the target of

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marketing has changed, which at first how the company to obtain new customers, has turned into how the company keeps its existing customers to be loyal to the company [20]. One of the strategies that can be used by the company is to utilize social media. The social customer is defined as a customer who uses social media to obtain and share information that related to a brand with others. This customer type is not the type of customers that passive[21]. They will not hesitate to tell their experiences with a certain brand whether they have pleasant or unpleasant experiences. This would be the reason why companies should participate in the use of social media, which is to maintain brand reputation [22].

3.1. Data Collection

The data were collected manually from various e-commerce websites such as Amazon, Flipkart, shopclues and so on. Initially, the research work predicts the brands preferences from popular e-commerce websites and then, predicts the customer loyalty on popular recognized and unrecognized products for 10 categories. Table 1 shows the categories and their popular recognized products and unrecognized products.

Table 1 : Different Categories of products from popular websites

Categories	Recognized product brands	Unrecognized product brands
Electronics	Philips, Dell, Lenovo, Samsung, HP	Andoer, Docooler, Leoie, TGK, RAISSER
Furniture	Indian Royals, Nilkamal, Cloudtail India, Peps India, Centuary Mattresses	Nikunj, SS Wood Furniture, EuroShop Retail, Bianca home, Dezire.
Clothing	Van Heusen, BIBA, Park Avenue, Allen Solly, Louis Phillippe	Oxemberg, Zivame, Monte Carlo, Levis, Fabindia.
Mobiles Accessories	JBL, Boat, Mivi, Zebronics, Flybot	PTron, ELV, Bobo, ADL, Muzili
Baby Products	Johnson and Jhonson, Himalaya, Mother Care, Biotique, MeeMee	Rustic Art, Sebamed, Farlin, chicco pure bio, Omved.
Home and Kitchen	Bajaj, Butterfly, Prestige, Kent, Pigeon	Nova, Bulfyss, Glun, Honeywell, Havells
Mobiles	Motorola, Redmi, Vivo, Nokia, Oppo	Micromax, Coolpad, Videocon, Realme, Lava
Watches	Timex, Rolex, Titian, Sonata, Fastrack	Lawman, enhance, Fossil,casio, Seiko.
Personal Care	Nivea, Dove, Biotique, Garnier, Ponds	Tresemme, L’Oreal Paris, Lancome,

After collecting the reviews from the websites, pre-processing should be carried out to improve the performance of the proposed method.

3.2. Pre-Processing:

Pre-processing the data is the process of cleaning and preparing the text for classification. Online texts contain usuallylots of noise and uninformative parts such as HTML tags, scripts and advertisements. In addition, on words level, man words in the text do not have an impact on the general orientation of it. Keeping those words makes the dimensionality of the problem high and hence the classification more difficult since each word in the text is treated as one dimension. Therefore, the data properly pre-processed: to reduce the noise in the text should help improve the performance of the classifier and speed up the classification process. The whole process involves several steps: online text cleaning, white space removal, expanding abbreviation, stemming, stop words removal, negation handling and finally feature selection.

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3.3. Transfer Learning

The pre-processed data are given as an input for finding the most preference brands of users from various e-commerce websites. The key idea in transfer learning is that new experiments should transfer insights from previous experiments rather than starts learning a new. Here, it is standard practice to train a neural network for one task and then use the trained network weights as initialization for a new task. The hope is that some basic low-level features of a vision system should be quite general and reusable. However, fine-tuning often fails to produce initializations that are uniformly good for solving new tasks. The researchers needs to fix this problem is a class of algorithms that seek to optimize Meta-Learning (ML) initialization weights. In these algorithms, one meta-optimizes over many experiments to obtain neural network weights that can quickly find solutions to new experiments. We will use the SLVG algorithm to learn initialization weights for brand estimation. Figure 2 shows the block diagram of ICDTL.

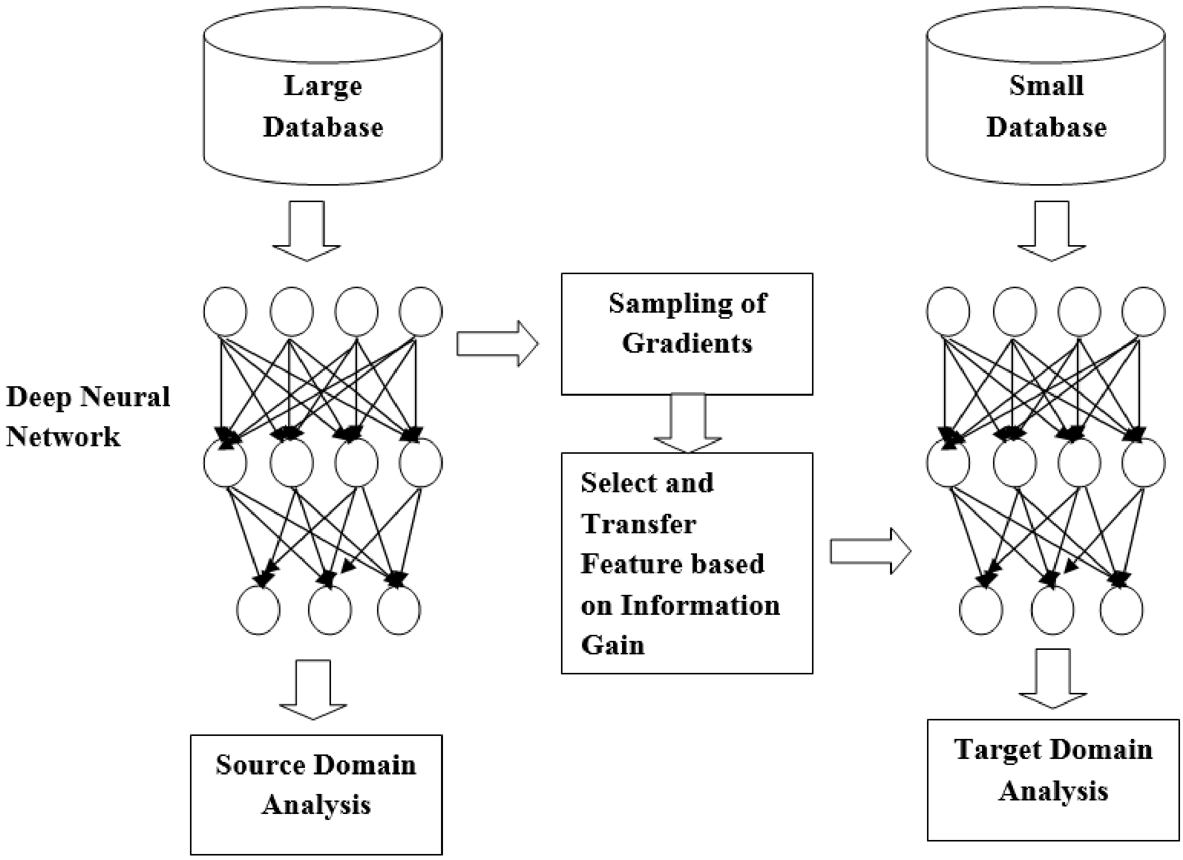

Figure 1: Block diagram of Proposed Transfer Learning

The optimization problem of ML should be considered by finding an initial set of parameters φ, such that for a randomly sampled task τ with corresponding loss L_τ , the learner will have low loss after k updates. The Eq. (1) are as follows:

$$\underset{\varphi}{minimize}\, E_\tau[L_\tau(U_\tau^k(\varphi))] \qquad (1)$$

Where, U_τ^k is the operator that updates φ k times using data sampled from τ. In few-shot learning, U corresponds to performing gradient descent or Adam on batches of data sampled from τ. ML solves a version of Equation (1) that makes on additional assumption: for a given task τ , the inner-loop optimization uses training samples

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A, whereas the loss is computed using test samples B. This way, ML optimizes for generalization, akin to cross-validation. Omitting the superscript k, the Eq. (1) is changed to Eq. (2)

$$\underset{\varphi}{minimize}\, E_\tau[L_{\tau,B}\left(U_{\tau,A}(\varphi)\right)] \quad (2)$$

ML works by optimizing this loss through stochastic gradient descent, i.e., computing. This can be shown in Eq. (3) and Eq. (4).

$$g_{ML} = \frac{\partial}{\partial_\varphi}\left[L_{\tau,B}\left(U_{\tau,A}(\varphi)\right)\right] \quad (3)$$

$$= U'_{\tau,A}(\varphi)L'_{\tau,B}(\tilde{\varphi}), \text{ where } \tilde{\varphi} = U_{\tau,A}(\varphi) \quad (4)$$

In Equation (4), $U'_{\tau,A}(\varphi)$ is the Jacobian matrix of the update operation $U_{\tau,A}$. $U_{\tau,A}$corresponds to adding a sequence of gradient vectors to the initial vector, i.e., $U_{\tau,A}(\varphi) = \varphi + g_1 + g_2 + \cdots + g_k$. In Adam, the gradients are also rescaled elementwise, but that does not change the conclusions. In next section, SLVG are discussed, which is used to train the features of the data.

3.4. Sampling Learning Vector Gradient

SLVG learns an initialization for the parameters of a neural network model, such that when these parameters are optimized at test time, learning is fast i.e., the model generalizes from a small number of examples from the test task. Similarly, this method use data from all experiments to learn weights, which are good initializers. By good initializers, we mean that starting from weight initialization, one can train neural networks to estimate the value for any arbitrary experiment much faster and with less data than starting from random initializations. To learn these good initializations, the proposed method use a transfer learning technique called SLVG.

The idea is to perform experiment-specific inner updates $U(\varphi)$ and then aggregate them into outer updates of the form $\varphi_{new} = \varepsilon \cdot U(\varphi) + (1 - \varepsilon) \cdot \varphi$. In this paper, we consider a slight variation of SLVG. In standard SLVG, ε is either a scalar or correlated to per-parameter weights furnished via stochastic gradient descent (SGD). For this research problem, the network layers should be encouraged to learn at different rates. The hope is that the lower layers can learn more general, slowly changing features, and the higher layers can learn comparatively faster features that more quickly adapt to new tasks after ingesting the stable lower-level features. To accomplish this, the path of least resistance are considered and make ε a vector which assigns a different learning rate to each neural network layer. Other than the stepsize parameter ε and task sampling, the batched version of SLVG is the same as the SimuParallelSGD algorithm [23]. SimuParallelSGD is a method for communication efficient distributed optimization, where workers perform gradient updates locally and infrequently average their parameters, rather than the standard approach of averaging gradients. From the output of the proposed ICDTL technique, key aspects are identified from the pre-processed data, which are to identify the relationship between customer loyalty and brand names for three major categories.

IV. RESULTS AND DISCUSSION

In this experimental setup, the proposed ICDTL method was implemented on a computer with 8GB RAM, Intel Core i5 with 2.2 GHz using Python 3.7.3. The validation of proposed ICDTL was verified using the pie-chart for both male and female for particular categories, which are collected from various on-line websites. The below section explains the data used for validating the ICDTL, quantitative and qualitative analysis of proposed method against existing techniques.

4.1. Description of Dataset

The data are collected from various online websites and several categories are presented in the review data. The proposed ICDTL method uses some of the major categories for validations, namely Home appliances, Fashions and Electronics. According to the product features and brand names, the user's loyalty can be easily identified.

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4.2. Analysis of Proposed Method on user's loyalty

In this section, pie-charts for male and female are presented according to different three categories such as electronics, home applications and fashions. From the figures, the recognized brands considers product features, brand names, advertising and satisfactions, where un-recognized brands considers the previous customer reviews, price, offers and quality of product.

4.2.1. Representation of user's Loyaltyon Electronics categories

In this analysis section, the loyalty of male and female on various categories such as electronics, fashion and home applications based on recognized and un-recognized brands. At first, the electronics category are analyzed and represented as Figure 2 and 3 for recognized and unrecognized brands on Electronics.

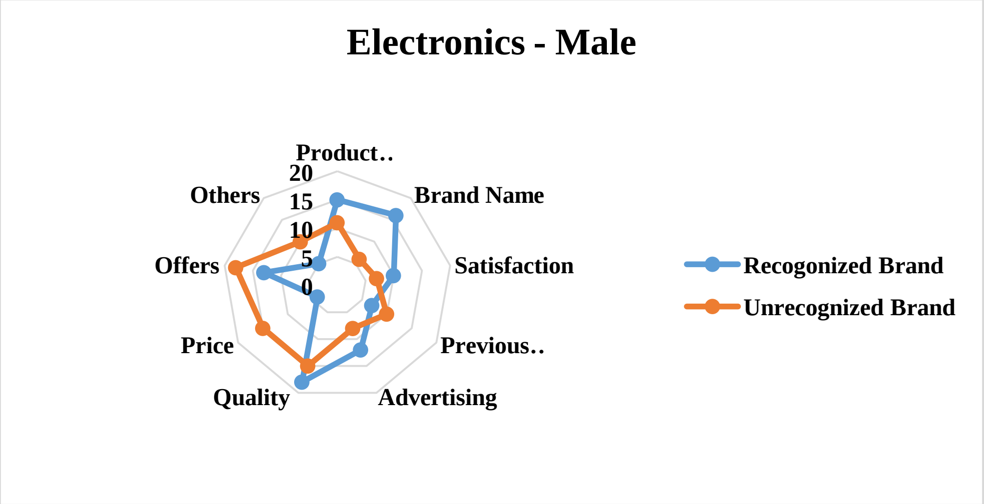

Figure 2: Recognized and Un-recognized brands on Electronics for Males' Loyalty

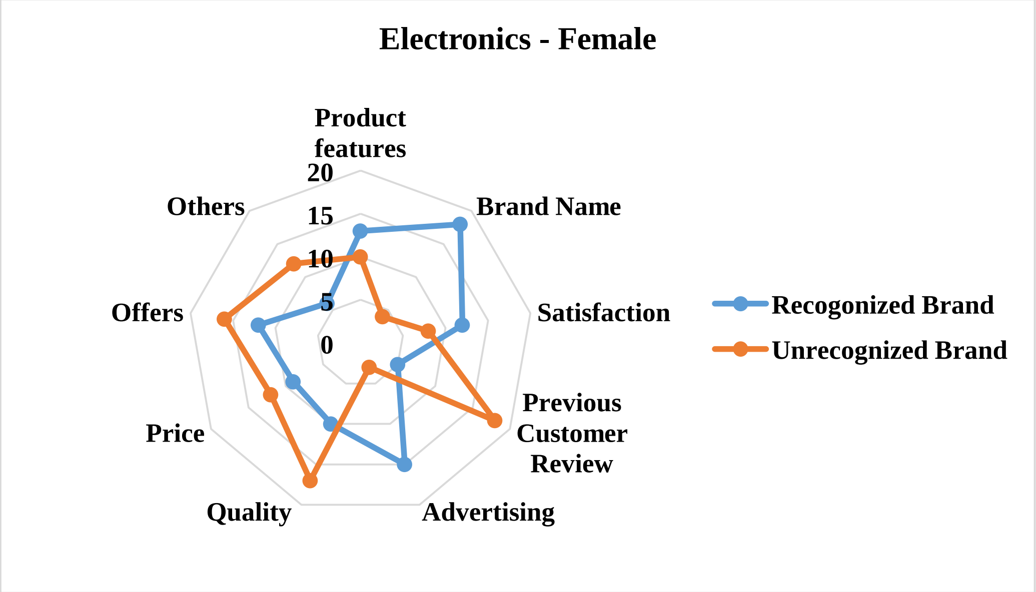

Figure 3: Recognized and Un-Recognized brands on Electronics for Females' Loyalty

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Major Findings from the category Electronics

- The male's loyalty on electronics are based on recognized brands, when compared to unrecognized brands. Because, males are majorly concentrated on product features, brand names and satisfaction.
- While concentrated on unrecognized brands, males considers more on previous customers reviews and offers in price. This is due to they have more interested on popular brands.
- The female's loyalty are mainly based on product features and brand names, but when compared with male, their loyalty levels are decreased. This is due to females are less concentrated on electronics.

4.2.2. Representation of user's Loyalty on Fashion categories

In the second experiments, the analysis of females and males loyalty on fashion category are depicted in Figure 4 and 5 for both recognized and unrecognized brands.

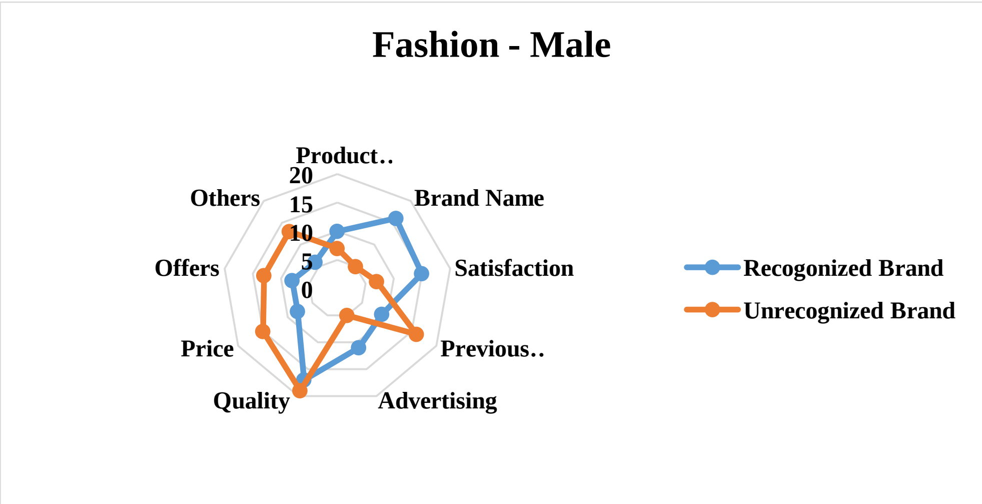

Figure 4: Recognized and Un-recognized brands on Fashion for Males' Loyalty

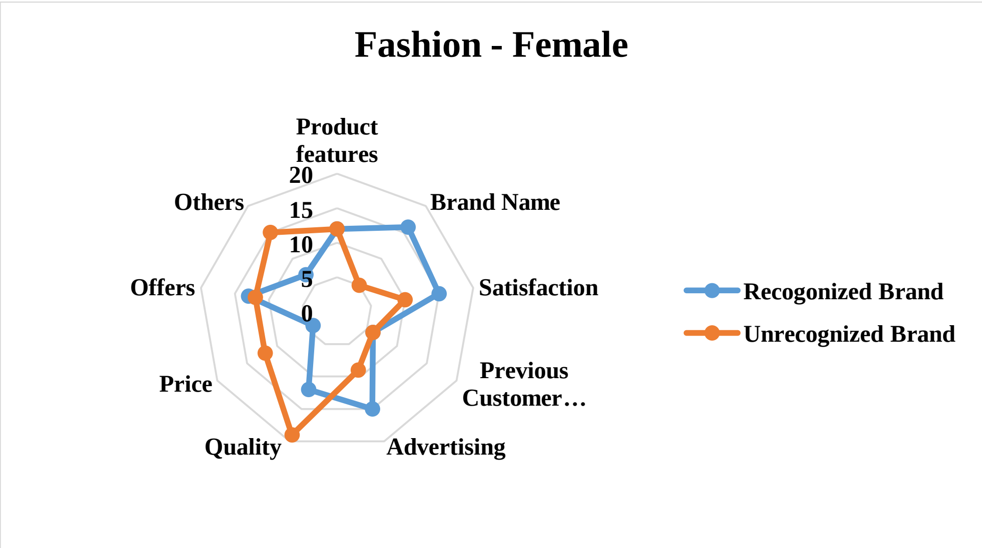

Figure 5: Recognized and Un-Recognized brands on Fashion for Females' Loyalty

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Major findings from the category Fashions

- In males' loyalty, the brand names, quality and satisfaction are majorly considered for recognized fashion category. But, offers, prices, quality of products and previous reviews are considered for unrecognized fashion category.
- From the experimental analysis, the male didn't consider product features for both recognized and unrecognized fashion category.
- When compared to males' loyalty, female loyalty on both fashion category provides better performance. The offers and product features attained higher performance for both fashion category.
- In fashion category, the recognized brand category achieved higher performance than unrecognized brand category. The prizes are majorly considered in both fashion category.
- Like man, females also didn't consider prices on both recognized and unrecognized fashion category.

4.2.3. Representation of user's Loyalty on Home Applications

Finally, the analysis of user's loyalty on home applications for both female and male are experimented and the graphical representations are presented in Figure 6 and Figure 7.

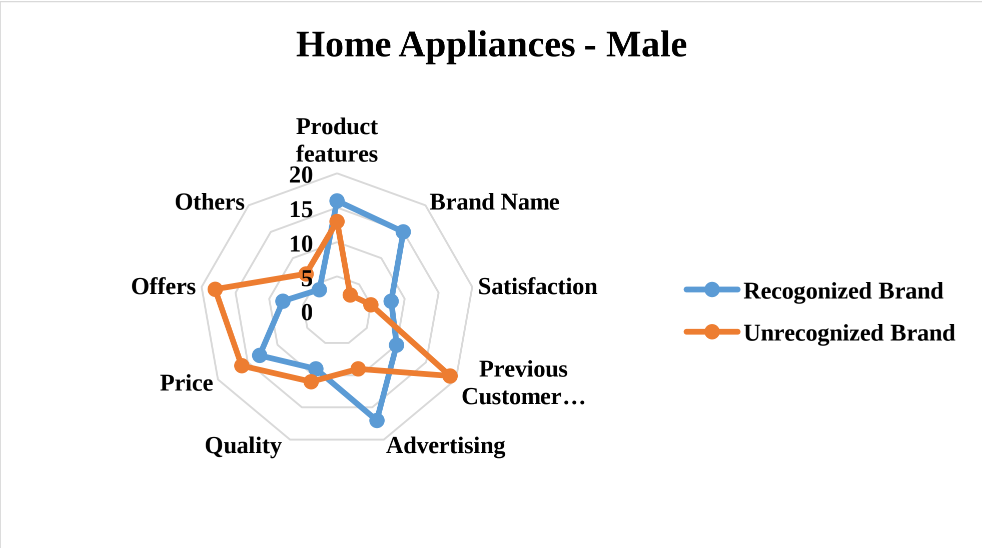

Figure 6: Recognized and Un-recognized brands on Home Applications for Males' Loyalty

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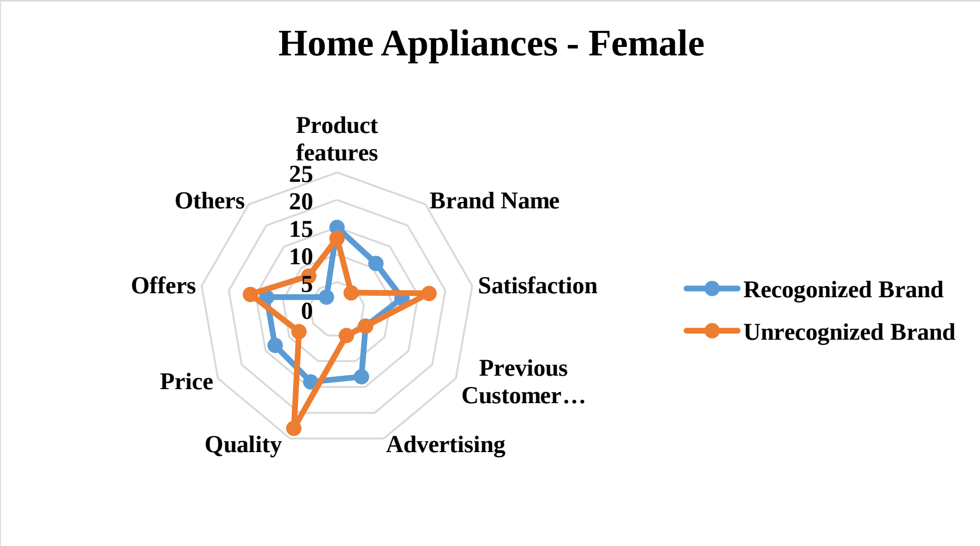

Figure 7: Recognized and Un-recognized brands on Home Applications for Females' Loyalty

Major Findings from the category Home Applications

- The offers prices, product features and previous customer reviews are majorly considered in the unrecognized home applications category in males' loyalty.
- In recognized category, males gave importance to product features, advertising and brand names. In both sections, males considered equality of prices for finding the best home applications,
- The females' loyalty on home applications are majorly depends on quality of products and satisfactions in both unrecognized and recognized features. But, they didn't considered brand names and advertising for unrecognized features.
- However, they considered brand names and prices in recognized home applications.

V. CONCLUSION

The members can easily join online communities using social network sites for preferring brands without any cost by uploading brand-related pictures and videos. Recently, the emergence of social media technologies has transformed the mode of communication between company and individuals. Despite of the popularity and the potential of brand communities as a useful communication and marketing tool especially in social networks, the researches in this area are very limited. So, this paper aimed to investigate the online brand communities, particularly with regard to social network sites, and give a better understanding of the importance characteristics of online brand communities through the lens of academic research. The proposed ICDTL technique through its efficient transfer of learned features paves a way to analyze the brand related behaviour with lesser data about the consumers during their purchase and their loyalty towards a brand with its reasoning in this digital era. By this a seller can able to easily understand the market needs and solutions to improve the business according to customer needs. In future, this research can be extended to analyze the seller features and match the customer needs to find out the gap between supply and demand service.

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