Trail for Unearthing Latent Consumer Behavior through Big Data Analytics

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Abstract- *With the increasing trend in market competition, the key to success shifts from products to the customers. Customer Relationship Management has become an emerging topic for enterprises which encourages relationship enhancement and focus on strengthening bonds with the customers. Being customer focus, helps an organization to better serve their customers thus leading to increased customer retention. In understanding customers, availability of vast amount of data is an advantage. With the advancement of technology, data is gathered from different places associated with different consumption contexts and therefore, big data has become one of the most vibrant technologies to obtain insights about the consumers. The increasing need for consumer behaviour analysis reforms the use of Big Data. Unique volume, velocity, and variety of primary data available from individual consumers provide behavioural insights about consumers, where marketers could translate those in gaining competitive advantage. But at present, big data analytics interprets the result to exhibit the "effect" rather than exploiting the "cause" behind. Consumers on the other hand are complex beings exhibiting results based on hidden constructs leading to different decisions. These hidden drivers are the latent behaviours of consumers and this paper proposes possible ways that technology can be utilized to unearth such hidden constructs.*

Keywords- *Big Data; Consumer Behavior; Personalities; Personality Identification; Data Analytics; Marketing Intelligence; Big Data Analytics;*

1. INTRODUCTION

Understanding consumer behavior paves the way for a successful business (Nelson, 1970). Marketing strives to understand the customers of a business for better exchange of values (Vinson, Scott, & Lamont, 1977)[63]. How well consumer pains are identified, determines how good a solution is, in bringing light to the deprivations. Consumer responses and their level of satisfaction is the ultimate test to determine the success of a marketing strategy (Sheth & Parvatlyar, 1995)[54]. Hence, knowledge about consumers should be incorporated into every facet of a successful market plan. With swiftly changing landscapes, gaining insights become paramount in agility of a business. This lets organizations to define their own market and successfully identify the threats and opportunities (Webster, 1992)[64].

Field of consumer behavior studies the processes involved when individuals select, purchase, use or dispose products, services, ideas or experiences to get the needs satisfied (Bettman & Ross, 1979)[6]. Consumer behavior resembles the actions of a stage play. People act out varying roles depending on the play. Same way consumers alter their consumption decisions depending on the particular play they belong to at a given point in time. The criteria used to evaluate products and services in one of the roles may differ from those used in another (Solomon, Dann, Dann, & Bennett, 2007)[57].

The S-O-R consumer involvement paradigm developed by Houston and Rothschild defines the interaction among different customer involvement mechanisms (situational, enduring and response), situations and decision-making processes (Jacoby, 2008[28]; Slama & Taschian, 1987)[56]. The model suggests a methodology to determine how the external stimuli influences a consumer to behave in a certain way (Chang, Eckman, & Yan, 2011)[11]. Social, product or communication characteristics stimulate the cognitive and emotional statuses of an organism thus affecting the purchase intentions, leading the organism to change responses based on the stimuli. Consumer responses heavily depend on the structure of the mind. i.e. various psychological constructs that process and interpret the stimuli. Therefore, it is important to know and model this structure or the 'Organism' to offer relevant solutions to the consumer. (Kim & Lennon, 2013)[36].

In the early stages of development, field of consumer behavior was known as field of "buyer behavior", emphasizing on the relationship that is formed between the customer and manufacturer at the time of purchase. But at present, consumer behavior is a node in the ongoing consumption process which exchanges values influencing the pre-post buying behaviors of a customer (Solomon et al., 2007)[57].

2. WHAT IS LATENT CONSUMER BEHAVIOR?

During the times of the world war, people had a balance in their life with simple and limited wants to fulfill their need of existence. Market research tools were at their preliminary stage as consumer behavior was primitive (Stoicescu, 2015)[58]. Marketers' prime intention was to determine the success of a product that is on offer. With the evolution in mankind, consumers had an open mind where they were likely to purchase new products often in large quantities. From primitive needs fulfillment, the society has now shifted to appearance and materialism needs based society (Vigneron & Johnson, 1999).

Today customer behavior has changed as they need instant value, mobile functionality and user- friendly services. Present day consumer minds are highly active and less tolerant to unfavorable solutions (Hirschman & Holbrook, 1982)[26]. Customers one to another act differently as they are more informed, socially networked and less loyal in nature.

In such an environment, how a consumer behaves is unpredictable, thus giving rise to latent consumer behavior. Latent behavior involves behavior that is not directly expressed via overt responses. This occurs naturally with no obvious behavior reinforcements (Jensen, 2006)[29]. Hence, unearthing these latent behaviors will provide answers for questions such as: why Amazon was chosen over Ebay, why ice-cream was chosen over chocolate and will John be interested in purchasing a fruit juice over a soft drink. In other words, "causality" is given more emphasis over the "effect". What and why of a consumer's behavior will be revealed than describing how the consumer behaved.

3. YESTERDAY'S METHODS OF CONSUMER PREDICTION

At the early stages of the 20th century, consumer behavior was analyzed through the studies conducted by polling (Szolnok & Hoffmann, 2013)[60], advertising and crowd sourcing strategies (Couper, 2011). The main intention of these marketing research techniques was to determine whether a product is worthwhile introducing and how good the product be embraced by the customers (Peter & Tarpey, 1975). Competition in the business world grew fierce with the evolution of human needs which in turn amplified the demand for products. This lit a light in the world of marketing signifying the need for qualitative and quantitative measures of getting to know the customer. The qualitative measures being focus groups, in-depth discussions and observational research while linear models, descriptive statistics and multivariate analysis being the quantitative methods (Stoicescu, 2015)[58].

In year 2013, Theory of Reasoned Action (TORA) and Net Promoter Score (NPS) were named the most successful methods of market research (see Mattox, 2013; Fishbein, 1979). The Theory of Reasoned Action was developed by Martin Fishbein and Icek Ajzen in 1975. This model predicts the behavioral intention, attitude and spanning predictions of attitude (Vallerand, Paul, Jean-Pierre, G., & Claude, 1992)[61]. Net Promoter Score is a customer loyalty metric developed by Fred Riechheld, Bain & Company and Satmetrix. This approach was made public in year 2003 at a business review article by Riechheld. NPS is an alternative to existing customer satisfaction research and depicts a correlation with company's revenue growth (Grisaffe, 2007)[20]. The questions are usually rated in a scale of 0-10 and the respondents are grouped accordingly. A typical question would take the form: "How likely would you recommend product X to a colleague?" High value for the indicator indicates high customer satisfaction (Gamble, Marsella, & Stone, 2005)[19].

Social networking has revolutionized the practice of community formation (He, Li, Liao, Song, & Cheung, 2016)[25]. Identification of latent behavior has made it possible to make personalized community recommendations based on behavior reflected via social media. Association Rule Mining (ARM) (see Charles & Aarthi, 2016; Chen, Chiu, & Chang, 2005) and Latent Dirichlet Allocation (LDA) (Krestel, Fankhauser, & Nejdl, 2009)[37] are two data mining techniques that cater behavior discovery in determining the probability of an individual becoming a part of a certain community on social media (Chen, Chu, Bai, Wang, & Chang, 2009)[12].

Classic customer analysis techniques were concerned about analyzing the behavioral intention of people but not the actual behavior as it was the easiest to find information about. Until recent, determining actual customer is tedious due to the emergence of the Internet, e-commerce and social media which has radically redefined the scope of consumer behavior. E-commerce web sites have replaced Point of Sale (POS) and cash registers, phone conversations with friends about products purchased are replaced by tweets and posts on social media which can be analyzed by anyone who follows those feeds and posts. In fact, everything and anything in today's world generate terabytes and petabytes of data waving hands for the emergence of new means of consumer behavior analysis. An intelligent data analyst today can gather information out of parking lots, toll booths, internet searches, social media activities and etc. as every human action today leaves a digital trace which can be recorded, processed and analyzed in revealing patterns and trends in them. Customers engage in their thoughts whilst the data analysts predict what customers would actually do. In this context, marketers should simulate both thoughts and behaviors of a consumer, to design marketing programs having considered what consumers think to produce desired consumer responses. This simulation is now possible with the availability of data on actual consumer behavior. The analytic techniques will only show the patterns but lack in revealing latent behaviors, as big data is mere data on responses. (Brosekhan, Velayuthsan, & Phil, 2003)[10].

4. BIG DATA IN TODAY'S CONTEXT

Big data is the combination of volume (massive amount of data), variety (diverse data), velocity (speed of data creation) and veracity (accurate data) (see Russom, 2011[51]; Srinivasa & Mehta, 2014; Walker, 2015). Big data is one of the four channels through which digital transformation happens including cloud, mobile and network platforms (Zakir, Seymour, & Berg, 2015)[67]. Big data is gigantic in existence unlike data warehouses. It contains data in all forms such as text, image, sound and video that collects information from a variety of input sources including sensors. More precisely this is data with potential when used in the right context (Rajaraman, 2016)[48].

The business community has initiated envisioning the growth of their businesses through big data integrations (LaValle, Lesser, Shockley, Hopkins, & Kruschwitz, 2011)[41]. According to Sven Denecken, the global vice president for cloud solutions: big data will drive business strategies, new product strategies and new customer relationships. Using the right data in the right context is a means of making smart decisions, exploiting new opportunities driving competition as the ultimate result (U. Fayyad, Piatetsky-Shapiro, & Smyth, 2004).

5. BIG DATA ANALYTICS AS AN INSTRUMENT FOR CONSUMER BEHAVIOR ANALYSIS

Decades ago, "analytics" referred to study of existing data to excavate potential trends and patterns in data. Today the struggle is discovering hidden information through vast amount of data, collected from varying sources (Fang & Li, 2014)[16]. There comes big data analytics into picture. Big data analytics is a trending technology, that significantly changes the way organizations deal with customer behavior data in generating insights. One such analysis involves customer behavior analysis (Khade, 2016)[34].

As an example, through a seasonality analysis companies could identify changes in buying patterns during seasons of a year thereby creating products and services to suit each season. A priority analysis determines the order in which customers purchase products and whether the order of one product selection involves any priority over another product on offer (Stoicescu, 2015).

Big data's most popular studies data mining techniques involve market basket analysis and cross selling analysis (see Olson, 2016)[45] These analyses determine the association among the products in the shopping cart of a customer (Berry & Linoff, 1997)[5]. This aid to bundle products when offering promotions and discounts. But, none explains the consumer intentions nor provide insights, rather surfaces a result pattern expressed by customers.

6. DATA ANALYTICS TO BETTER UNDERSTAND THE AUDIENCE

Customer preferences are subjected to constant change and data analytics is a reliable tool for collecting and processing information on consumer behavior and consumer buying habits. Big data provides measurable metrics and intelligence (Marr, 2015)[42] to businesses which enables creation and development of products and services much relevant to the targeted audiences (Demirkan & Delen, 2013)[14]. But the information must be curated and organized to get a better view of consumer behavior (Zhou, Chawla, & Jin, 2014). Through predictive models such as audience segmentation, a business can monitor buying habits to distinct old customers from new ones and to distinct repeat customers from single purchase ones (Roberts & Lilien, 1993)[49]. This process involves several steps.

- Customers are grouped according to their buying behavior and their preferences. Through which new segments are created with the intention of creating more targeted products and services.
- Social data intelligence aids in understanding how and how good consumers engage with the business and its brands. Level of loyalty can be measured through this.
- Intelligent tools and techniques are used in mining big data to generate better customer insights and deliver targeted advertisements to each identified market segment.

Customer personas are characteristics that represent variations in customer bases (Khalid & Helander, 2006)[35]. They carry information about demographics, sources of influence, motivators and income. Based on these types of personas, big data tinkers with them in generating certain metrics which helps a business to understand their customers more.

- Average purchase size – How much does a customer spend on purchase?
- Lifetime Value – How strong is the relationship between a company and its customers?
- Acquisition cost – How much a company has spent on marketing communication and sales in order to acquire these customers?
- Retention cost – What do customers expect from the business to be loyal?
- Customer delightness – Are the customer happy and satisfied with the current offerings of the company?
- Value alignment – Are the intended core customers really making purchases from the company?

Data analytics helps to derive more intelligent information from big data on consumer behavior and impressions of a business. Big data analytics provide resources to enable measuring how competently a business addresses consumer needs at any given point in time. All these finding will purely be based on the resulting data and big data.

7. PREDICTION OF CONSUMER BEHAVIOR

Predictive analytics work to determine the strategies which is most likely to generate the desired response and then to differentiate the commercially supported interactive surrounding accordingly (Shmueli & Koppius, 2011)[55]. This process aids in identifying the latent behavior of consumers. This implies that customers do only what they need with the added feature that such choices are made freely.

Success of product diffusion depends on how well the consumers are known by a business (Robertson & Kennedy, 1968)[50]. Knowing a consumer involves the ability of a business to predict the reaction of the consumer towards a prospective environment, based on behavior exhibited in the present world (Weiss & Indurkhya, 1998)[65].

7.1 Personality in Consumer Behaviour

Consumer behavior is a combination of complex psychological processors such as personality, perception, attitudes, emotions, and cognitive resource allocations. Even though consumer behavior refers to purchase of a product, in the context of consumer psychology, this refers to information search relevant to purchase decision, retail outlet or vendor selection and actions performed prior and after the purchase (Ajzen, 2008)[1]. Hence, understanding the influence of the above factors is a key to success in obtaining marketing intelligence.

Study of emotions provide insights about the feelings of a consumer before and after a product is purchased (Laros & Steenkamp, 2005)[40]. The attitude is the predisposition i.e. the stored decision about anything that is going to be used to evaluate before the perception (Katz, 1960)[33]. Attitudes may change and new are formed after perceptions. Perception describes how a consumer grasp the external world by organizing and interpreting the stimuli (Bokulich, Renn, & Massimi, 2016)[9]. i.e. how the world is constructed by a consumer (Elliott & Wattanasuwan, 1998). Personality depicts individual characteristics, patterns of thinking, feeling that determines certain ways of responding (Hogan, 2009).

Hence, it can be concluded that the personality is a set of traits and it can be used as one of the doors to get to understand latent constructs behind consumer responses (Allport, 1931)[2]. The personality of a person makes him to behave in a certain manner and this personality is reflected via emotions, attitudes and perceptions. This gives rise to personality assessment as an important subject in consumer behavior.

Personality assessment focuses on two broad areas (Kassarjian, 1971)[32].

1. Understanding individual differences in certain personality characteristics such as sociability or irritability
2. Understand how various parts of a person combine as a whole in making life's decisions

Biological and social characters both are needed in developing personality.

As per the psychoanalytical theory of Freud the three interacting forces Id, Ego and Superego interact together to produce behavioral patterns, personality, interests, motives and attitudes of people (see Harold H. Kassarjian, 1971). Id drives all psychic energy of a person. Superego is the internal representative of self - derived values of a person. The ego drives the Id and Superego to create rich variety of personal characteristics. These characteristics account for the purchase of a four door Sedan rather than a Porsche. The ego reasoning to all consumer behaviors are defended by rationalization, projection, identification and repression. The Stimulus Response theory utilizes these human characteristics in unveiling certain latent consumer behaviors. This theory sees personality as a conglomerate of habitual responses acquired through life maturity over time. Habits can be formed, changed, replaced or even broken. A driven stimulus will always generate a response. Habits are learned through rewarded responses where unrewarded responses are extinguished. Complex behaviors such as consumer behavior are learnt in a similar manner. Hence, people's personality plays an important role in determining the latent behavior of consumers.

People's personality types are characterized by five factors as per psychology (Barrick & Mount, 1991)[4]. Openness resembles people enjoying adventure. Conscientiousness reflects organized and methodical individuals. Extraverts are assertive in nature. People with agreeableness nature are kind and friendly. Neuroticism reflects less emotionally stable, moody and tense individuals (Judge, Heller, & Mount, 2002)[30].

8. UNEARTHING LATENT CONSUMER BEHAVIOR

As per the social theorists the human behavior can be categorized as compliant, aggressive and detached (Slama & Taschian, 1987)[56]. The socialist, Cohen states that compliant types are the ones who prefer brand names and use more of mouth wash and toilet soap. Aggressive type tends to use more razors than electric shavers, uses more of cologne, deodorant and after shave. Detached types are rarely driven by brand names. These people do not respond attractively to branding. Matching the social theories to real life context reveals that people who use razors are not always aggressive and this decision can be influenced by the type of the skin and their ability of purchasing electric shavers. People living in hot climate countries tend to use colognes and deodorants in a daily basis to keep themselves fresh and out of odor. The smell of the colognes they use may imply the assertiveness or the neutrality of that person (but also see Harold H. Kassarjian, 1971[32]; Bandura, 1999).

The aggressiveness or the need for achievement within people can be measured through personality testing instruments such as questionnaires, ratings and tests. Aggressive personalities are excluded from the non -

aggressive ones through analysis done on the responses provided by the target objects. People responding in equal manner are categorized, grouped and tagged with one personality label. The trait and factor theory believes using these instruments as the effective way to gauge the personal characteristics of a large audience. But this assumption is proved false when people attempt these with the intention of impersonating. Consumers' personality cannot always be identified through quantitative measurements (but also see Lahmann Stanley, 1970).

Gordon's personal profile purports to measure the correlation between ascendency, responsibility, emotional stability and sociability together with the consumption of headache remedies, vitamins, mouth wash, alcoholic drinks, automobiles, chewing gum and the level of acceptance of new fashion. Emotionally unstable people tend to consume a lot of headache remedies followed by alcoholic drinks or other drugs. People suffering from different moods tend to chew gum all the time to get rid of the stress generated and are most of the times addicted to gaming and social loafing. Hence there exists very high correlation among the above two discussed factors. People with from disturbed minds tend to do a lot of shopping and be up-to-date with it as a mode of stress relief and to extinguish the vulnerability of acceptance (see Harold H. Kassarjian, 1971).

Further the Gordon's personality profile excavates a relationship between the smokers and compliance needs. Cigarette smokers are positively related to sex dominance, aggressiveness and have a raging need for achievement. But a negative relationship with compliance needs (see J. Walter Thompson, 1977).

California personality inventory brought a new dimension to personality analysis with the introduction of paper – and – pencil test. As per Robertson and Myer, a personality can be innovative or an open leadership. Open leadership is characterized by gregariousness and venturesome. Innovativeness is characterized by social participation, cosmopolitan and perceived risk. Both these personalities react positively to new products in the market (but also see Harold H. Kassarjian, 1971). Robertson and Mayer state that innovativeness determines the personality of a person. This can be concluded as a false assumption in matching with real world contexts. Being innovative is a state of mind deserved partially at birth and majority being learnt whereas personality is learnt and made after birth over time space. This theory further states that more masculine a person's personality, the more masculine the image of his regular brand of cigarettes, perfumes, cars and alcoholic drinks are.

Thurstone Temperament Schedule which is a replica of Evans's study focuses on the personality of automobile owners. Car owners of compact and standard cars have shown similar personalities while owners of convertible and standard cars have shown contrasting personalities (Edward L. Grubb & Grathwohl, 1967).

Theory of self and self-concept views that individuals have a real self and an ideal self (Edward L Grubb & Stern, 1971). This theory aims to reveal the self-actions reflected through purchase of products and services (Edward L. Grubb & Grathwohl, 1967). Individuals perceive products they own or they want to have in terms of the symbolic value to them (Landon, 1974)[39]. Congruence between self and symbolic value is highly appreciated. As an example: a Porsche is extravagant and wealthy automobile. A consumer's self-image implies greater ownership of such products or brands. Study conducted by Jacobson and Kassoff divides individuals into two categories based on their self-image on automobiles. People being called cautious conservatives prefer small cars due to economic convenience. Confident explorers prefer large cars as they want to express their ability to control the environment. This individual segment is more aggressive in nature, more masculine, extravagant, suffers from the need of expressing wealth and has high perception about themselves. In general, the theory says that an automobile owner's perception about of his car is essentially congruent with his perception of himself (Birdwell, 1968)[8].

Another theory of self, expressed by Grubb, found a personality similar to confident explorers within beer drinkers. Beer drinkers find themselves more confident, temperamental, social, extraverted, forward, sophisticated and impulsive. But drinkers and non-drinkers have perceived brands similarly which is a contradiction to the theory stated by Grubb. A beer drinker can perceive above stated characteristics due to instability of mind created through disturbances showing the personality neuroticism. The person may not be a regular drinker as such. Hence, it is still too early to categorize an alcoholic as an extravert or neuroticism (Baker, 2001)[3]. In the latter part of theory development, Hamm and Cundiff related a product perception with self- actualization. Self-actualization is the discrepancy between self and ideal self. High self-actualizers define themselves in terms of house luxury, automatic dishwasher, art printers and high focus on dress. Low self-actualizers in contrast are the segment that appreciates TV dinners and participated in alcohol consumption (Hamm & Cundiff, 1969)[24]. As per the backward segmentation of Wells's, individuals can be clustered into behavioral characteristics based on their personality to generate correlations among products and consumer behavior (Kucukemiroglu, 1999)[38].

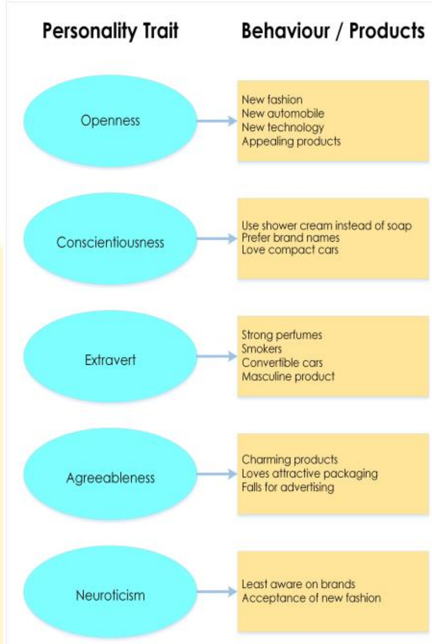

Fig 1: Framework of Association among Personality & Purchase

8.1 Role of Big Data

Big data is the key input for data driven decision making (Provost & Fawcett, 2013)[47]. Data driven decision making is highly dependent on accurate and timely information as failure to obtain such information creates business failures.

Data driven decisions are better decisions as big data allows managers to make decisions based on evidence rather than on intuition. Hence, big data has the potential to revolutionize the business world thus giving birth to digital organizations (McAfee & Brynjolfsson, 2012).

Except for digitally born companies such as Google and Facebook; for supermarkets, big data comes in handy to analyze the data collected through loyalty card systems. Consumers' purchase records can be analyzed to determine the matrix of products that is purchased at a given instance of visit and such product matrices analyzed over a considerable period of time to exhume the major preferences. These preferences can be matched against the framework created above to determine the personality type of the person. This personality determination aids in introducing products that suit the emotional level and mind stability of a person. Furthermore, personality determination uncovers the barriers of consumer profiling and succeeds in generating the story about a business's customers. Discovery of associations are important, and we use big data analytics to cater this purpose. However, associations in responses are not what is pitched at, but rather a manifestation for the deeper level of consumer drivers.

Clustering and classification are big data mining techniques, that are widely in use (Russom, 2011)[51]. Classification techniques such as Naïve Bayes, decision forest, logistic regression and SVM (Ngai, Xiu, & Chau, 2009)[44] (Usama Fayyad, Piatetsky-Shapiro, & Smyth, 1996) can be used in grouping customers based on behavior similarity exhibited as shoppers. Thus, formed classes can be subjected to content based filtering and collaborative filtering with the help of map reduce in big data analytics (Zhao & Shang, 2010)[68], to recommend products that suits their personality. Content based recommendation creates profiles for both products and users to match a user with a product rather than matching cross selling products and recommending to every user, which is the case at present. Collaborative filtering segments users based on the behavior shown in making purchases through latent class analysis modelling approach (Bhatnagar & Ghose, 2004[7]; Swait, 1994)[59]. Through these recommendation systems; consumers being overloaded with data, need for complex searches and irrelevant product matches can greatly be reduced (Xiao & Benbasat, 2007)[66] thus establishing the need for consumer personality identification.

8.2 Added Advantage of Data Analytics to Business

Amongst the many advantages that can be gained from data analytics, a few are mentioned below.

- Leveraging mobile data such as location and accompanying with insightful analytics to excavate interests and needs of people there by creating new opportunities to increase revenue (Gupta & George, 2016)[23].
- Business intelligence garnered through good analytics of big data and customer interaction metrics allows businesses to better influence process automation in businesses there by concentrating on decision science

to improve efficiency and effectiveness (Sagiroglu & Sinanc, 2013)[52].

- Systems that integrate mobile-focused biometrics together with customer digital footprint provoke an experience which is better streamlined and secured. The advantage is that the customer can choose the method of interaction as Web, mobile application, or voice/video which best fits their personal preferences. The capability of naturally serving the incongruent devices and methods, while still leveraging into a common customer platform, provides long lasting customer satisfaction that increases retention, acquisition and overall business profitability (Kambatla, Kollias, Kumar, & Grama, 2014)[31].

9. FUTURE DIRECTIONS

The ultimate purpose of this paper is to bring into the limelight the importance of understanding latent consumer behaviour in any attempt to draw Marketing Intelligence from Big Data. However, the paper does not suggest a framework-like steps to make such intelligence drawing possible. Hence, the next step is to develop a comprehensive framework that enables mining consumer latent behaviors. This leads to three other important steps as mentioned below;

- Methods for describing consumer behavior models that are developed by scholars from associated disciplines outside of Information Technology. for proper integration with the systems that adopt the above proposed framework.
- Developing A Behavioral Query Language (BQL) to query knowledge related to a variety of consumer behaviors considering consumer-behavior modals
- Introducing a mechanism for capturing information consumptions and dynamically linking them with the BQL.

10. CONCLUSION

Consumer behavior has been an area of study since decades ago and today it is the center of focus for any business. With evolving technology, the tools and techniques used in consumer behavior analysis have developed tremendously. Today, the only process that can create a sophisticated but complete image of what consumers purchase and why they purchase them, is big data. Studies on big data reflect that tomorrow this technique of data analysis is a must for companies for their survival in the dynamic and digitized business world (Schiffman & Kanuk, 2002)[53].

Customer data intelligence empowers businesses by providing meaningful data for analysis of consumer behavior and business performance. Valuable data thus collected from all internal and external sources of information helps to drive business growth while aiding businesses to direct their limited marketing resources towards business strategies that results in highest conversion, engagement and sales (Schiffman & Kanuk, 2002)[53]. However, analytics done as of now greatly lack deeper level understanding spanning beyond the relationships between the results. This paper brings about the possibilities of using existing analytics for getting into deeper consumer insights that drive decisions.

11. REFERENCES

[1] Ajzen, I. (2008). Consumer attitudes and behavior. In C. P. Haugtvedt, P. M. Herr, & F. R. Kardes (Eds.), *Handbook of consumer psychology* (pp. 525-548). London, London: Lawrence Erllbaum Associates.

[2] Allport, G. W. (1931). What is a trait of personality. *The Journal of Abnormal and Social Psychology, 25*(4), 368-372.

[3] Baker, M. J. (2001). *Marketing: Critical Perspectives on Business and Management*: Routledge.

[4] Barrick, M. R., & Mount, M. K. (1991). The big five personality dimensions and job performance: A meta-analysis. *Personnel psychology, 44*(1), 1-26.

[5] Berry, M. J., & Linoff, G. (1997). Data Mining Techniques: For Marketing, Sales, and Customer Support *Data Mining Techniques*. New York, USA: John Wiley & Sons, Inc.

[6] Bettman, J. R., & Ross, I. (1979). Reviewed Work: An Information Processing Theory of Consumer Choice. *Journal of Marketing, 43*(3), 124-126.

[7] Bhatnagar, A., & Ghose, S. (2004). A latent class segmentation analysis of e-shoppers. *Journal of Business Research, 57*(7), 758- 767

[8] Birdwell, A. E. (1968). A Study of the Influence of Image Congruence on Consumer Choice. *The Journal of Business, 41*(1), 76- 88.

[9] Bokulich, A., Renn, J., & Massimi, M. (2016). *Boston Studies in the Philosophy and History of Science*: Springer Nature.

[10] Brosekhan, A. A., Velayuthsan, M., & Phil, M. (2003). Consumer Buying Behavior - A literature review. *Journal of Business and Management, 01*.

[11] Chang, H.-J., Eckman, M., & Yan, R.-N. (2011). Application of the Stimulus-Organism-Response model to the retail environment: the role of hedonic motivation in impulse buying behavior. *21*(3), 233-249.

[12] Chen, W.-Y., Chu, J.-C., Bai, H., Wang, Y., & Chang, E. Y. (2009). *Collaborative filtering for orkut communities: discovery of user latent behavior.* Paper presented at the 18th international conference on World wide web Pages, Madrid.

[13] Couper, M. P. (2011). The Future of Modes of Data Collection. *Public Opinion Quarterly, 75*(5), 889–908.

[14] Demirkan, H., & Delen, D. (2013). Leveraging the capabilities of service-oriented decision support systems: Putting analytics and big data in cloud. *Decision Support Systems, 55*(1), 412-421

[15] Elliott, R., & Wattanasuwan, K. (1998). Consumption and the Symbolic Project of the Self. *ACR*

European Advances.
[16] Fang, Z., & Li, P. (2014). The mechanism of" big data" impact on consumer behavior. *American Journal of Industrial and Business Management, 4*(1), 45.
[17] Fayyad, U., Piatetsky-Shapiro, G., & Smyth, P. (1996). From Data Mining to Knowledge Discovery in Databases. *AI Magazine, 17*(3), 37-54.
[18] Fayyad, U., Piatetsky-Shapiro, G., & Smyth, P. (2004). From data mining to knowledge discovery in databases. *American Association for Artificial Intelligence*, 37-54.
[19] Gamble, P. R., Marsella, A., & Stone, M. (2005). *Marketing Revolution.* Paper presented at the Kogan Page Limited.
[20] Grisaffe, D. B. (2007). Questions about the ultimate question: Conceptual considerations in evaluating reichheld's net promoter score (nps). *Journal of Consumer Satisfaction, Dissatisfaction and Complaining Behavior, 20*, 36-53.
[21] Grubb, E. L., & Grathwohl, H. L. (1967). Consumer Self-Concept, Symbolism and Market Behavior: A Theoretical Approach. *Journal of Marketing, 31*(4), 22-27. doi:10.2307/1249461
[22] Grubb, E. L., & Stern, B. L. (1971). Self-concept and significant others. *Journal of Marketing Research, 8*(3), 382-385.
[23] Gupta, M., & George, J. F. (2016). Toward the development of a big data analytics capability. *Information & Management, 53*(8), 1049-1064
[24] Hamm, B. C., & Cundiff, E. W. (1969). Self-Actualization and Product Perception. *Journal of Marketing Research, 6*(4), 470-472. doi:10.2307/3150085
[25] He, J., Li, X., Liao, L., Song, D., & Cheung, W. K. (2016). *Inferring a Personalized Next Point-of-Interest Recommendation Model with Latent Behavior Patterns.* Paper presented at the Thirtieth AAAI Conference on Artificial Intelligence.
[26] Hirschman, E. C., & Holbrook, M. B. (1982). Hedonic Consumption: Emerging Concepts, Methods and Propositions. *Journal of Marketing, 46*(3), 92-101.
[27] Hogan, R. (2009). What Is Personality Psychology? *An International Journal for the Advancement of Psychological Theory 9*(2), 152-153.
[28] Jacoby, J. (2008). Stimulus- Organism-Response Reconsidered: An Evolutionary Step in Modeling (Consumer) Behavior. *Journal of Consumer Psychology, 12*(1), 51-57.
[29] Jensen, R. (2006). Behaviorism, Latent Learning, and Cognitive Maps: Needed Revisions in Introductory Psychology Textbooks. *The Behavior Analyst, 29*(2), 187–209.
[30] Judge, T. A., Heller, D., & Mount, M. K. (2002). Five-factor model of personality and job satisfaction: A meta-analysis. *Journal of Applied Psychology, 87*(3), 530-541.
[31] Kambatla, K., Kollias, G., Kumar, V., & Grama, A. (2014). Trends in big data analytics. *Journal of Parallel and Distributed Computing, 74*(7), 2561-2573.
[32] Kassarjian, H. H. (1971). Personality and Consumer Behavior: A Review. *Journal of Marketing Research, 8*(4), 409-418.
[33] Katz, D. (1960). The functional approach to the study of attitudes. *Public opinion quarterly, 24*(2), 163-204.
[34] Khade, A. A. (2016). Performing customer behavior analysis using big data analytics. *Procedia computer science, 79*, 986-992.
[35] Khalid, H. M., & Helander, M. G. (2006). Customer Emotional Needs in Product Design. *Concurrent Engineering, 14*(3), 197- 206.
[36] Kim, J., & Lennon, S. J. (2013). Effects of reputation and website quality on online consumers' emotion, perceived risk and purchase intention: Based on the stimulus- organism- response model. *Journal of Research in Interactive Marketing, 7*(1), 33-56.
[37] Krestel, R., Fankhauser, P., & Nejdl, W. (2009). *Latent dirichlet allocation for tag recommendation* Paper presented at the Proceedings of the third ACM conference on Recommender systems, New York.
[38] Kucukemiroglu, O. (1999). Market segmentation by using consumer lifestyle dimensions and ethnocentrism: An empirical study. *European Journal of Marketing, 33*(5/6), 470-487.
[39] Landon, E. L. (1974). Self Concept, Ideal Self Concept, and Consumer Purchase Intentions. *Journal of Consumer Research, 1*(2), 44-51.
[40] Laros, F. J. M., & Steenkamp, J.-B. E. M. (2005). Emotions in consumer behavior: a hierarchical approach. *Journal of Business Research, 58*(10), 1437-1445
[41] LaValle, S., Lesser, E., Shockley, R., Hopkins, M. S., & Kruschwitz, N. (2011, Winter). Big Data Analytics and the path from insights to value. *MIT SLOAN Management Review, 52,* 21-31.
[42] Marr, B. (2015). Big Data. *Using SMART big data, analytics and metrics to make better decisions and improve performance*.
[43] McAfee, A., & Brynjolfsson, E. (2012). *Big Data: The Management Revolution*. Retrieved from Nelson, P. (1970). Information and Consumer Behavior. *Journal of Political Economy, 78*(2), 311-320.
[44] Ngai, E. W. T., Xiu, L., & Chau, D. C. K. (2009). Application of data mining techniques in customer relationship management: A literature review and classification. *Expert Systems with Applications, 36*(2), 2592-2602
[45] Olson, D. L. (2016). *Descriptive Data Mining*: Springer Singapore.
[46] Peter, J. P., & Tarpey, L. X. (1975). A Comparative Analysis of Three Consumer Decision Strategies. *Journal of Consumer Research, 2*(1), 29–37.

[47] Provost, F., & Fawcett, T. (2013). Free AccessOpen Access license Data Science and its Relationship to Big Data and Data-Driven Decision Making. *Big Data, 1*(1).

[48] Rajaraman, V. (2016). Big data analytics. *Resonance*, 695–716.

[49] Roberts, J. H., & Lilien, G. L. (1993). Chapter 2 - Explanatory and predictive models of consumer behavior *Handbooks in Operations Research and Management Science* (Vol. 5, pp. 27-82): Elsevier B.V.

[50] Robertson, T. S., & Kennedy, J. N. (1968). Prediction of Consumer Innovators: Application of Multiple Discriminant Analysis. *Journal of Marketing Research, 5*(1), 64-69. doi:10.2307/3149795

[51] Russom, P. (2011). *Big Data Analytics*: The Data Warehousing Institute.

[52] Sagiroglu, S., & Sinanc, D. (2013). Big data: A review. *international Conference on Collaboration Technologies and Systems (CTS)*.

[53] Schiffman, L. G., & Kanuk, L. L. (2002). *Consumer Behavior*. New Delhi, India: Pearcon Education.

[54] Sheth, J. N., & Parvatlyar, A. (1995). Relationship Marketing in Consumer Markets: Antecedents and Consequences. *Journal of the Academy of Marketing Science, 23*(4), 255-271.

[55] Shmueli, G., & Koppius, O. R. (2011). Predictive Analytics in Information Systems Research. *MIS Quarterly, 35*(3), 553-572. doi:10.2307/23042796

[56] Slama, M. E., & Tashchian, A. (1987). Validating the S-O-R paradigm for consumer involvement with a convenience good. *Journal of the Academy of Marketing Science, 15*(1), 36-45.

[57] Solomon, M. R., Dann, S., Dann, S., & Bennett, R. R. (2007). Consumer behavior as a field of study. In P. Burges, C. Robson, J. Davis, & K. Lamberton (Eds.), *Consumer behavior* (pp. 27-30). Frenhs Forest, Australia: Pearson Education

[58] Stoicescu, C. (2015). Big Data, the perfect instrument to study today's consumer behavior *Database Systems Journal 6*(3), 28-41.

[59] Swait, J. (1994). A structural equation model of latent segmentation and product choice for cross-sectional revealed preference choice data. *Journal of retailing and consumer services, 1*(2), 77-89.

[60] Szolnok, G., & Hoffmann, D. (2013). Online, face-to-face and telephone surveys—Comparing different sampling methods in wine consumer research. *Wine Economics and Policy, 2*(2), 57-66.

[61] Vallerand, R. J., Paul, D., Jean-Pierre, C., G., P. L., & Claude, M. (1992). Ajzen and Fishbein's theory of reasoned action as applied to moral behavior: A confirmatory analysis. *Journal of Personality and Social Psychology, 62*(1), 98-109.

[62] Vigneron, F., & Johnson, L. W. (1999). A Review and a Conceptual Framework of Prestige-Seeking Consumer Behavior. *Academy of Marketing Science Review, 1*(1), 1-15.

[63] Vinson, D. E., Scott, J. E., & Lamont, L. M. (1977). The Role of Personal Values in Marketing and Consumer Behavior. *Journal of Marketing, 41*(2), 44-50.

[64] Webster, F. E. (1992). The Changing Role of Marketing in the Corporation. *Journal of Marketing, 56*(4), 1-17.

[65] Weiss, S. M., & Indurkhya, N. (1998). *Predictive Data Mining: A Practical Guide*: Elsevier Science.

[66] Xiao, B., & Benbasat, I. (2007). E-commerce product recommendation agents: use, characteristics, and impact *MIS Quarterly, 31*(1), 137-209.

[67] Zakir, J., Seymour, T., & Berg, K. (2015). Big Data Analytics. *Issues in Information Systems, 16*(2), 81-90.

[68] Zhao, Z.-D., & Shang, M.-s. (2010). *User-Based Collaborative-Filtering Recommendation Algorithms on Hadoop*. Paper presented at the Third International Conference on Knowledge Discovery and Data Mining, Phuket.

[69] Zhou, Z.-H., Chawla, N. V., & Jin, Y. (2014). Big Data Opportunities and Challenges: Discussions from Data Analytics Perspectives. *IEEE Computational Intelligence Magazine, 9*(4), 62 - 74.