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The Influence of Personality Traits on Digital Quotient: An Indian Metro City Perspective

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Abstract: The measure of awareness, responsiveness, and adoption of emerging digital technologies is commonly referred to as the individual's digital quotient. As computing & digital technologies evolved, researchers also focused on drivers of user engagement towards digital platforms. The TAM and big 5 personality traits were leveraged to identify finer aspects of platforms design, offerings and influence of user behaviors. However, the studies were largely technology platform centric whereas this study provides end user centric analysis and identifies key personality traits that may influence an individual's digital quotient. An exploratory study was conducted in three Indian metro cities with high internet penetration. A diversified group of 83 participants actively contributed during a 12-month period ending in June 2020. The analysis used the natural language processing (NLP) methods, word cloud models, relevance scores and technologies to work on text mining and keyword extraction. The study concluded with a taxonomy theoretical framework of seven personality traits called UCCCEEE (updated, confident, connected, curious, experimentative, efficient, and epicurean). The study may help individuals & organizations to align to the fast evolving digital eco system. State governance, corporates and societies at large can leverage this to build talent and societal characters towards the digital economy respectively.

Keywords: Digital Quotient, Personality traits, Digital Awareness, Online Behavior, Digital Transformation

1. Introduction

Global internet usage reached 4.57 billion in 2020, with a penetration of 62% [1]. Online platforms are being leveraged as a key medium, by sellers of goods & services to outreach end users globally. In 2019, the gross merchandise value (GMV) of online commerce amounted to USD 3.53 trillion and is forecast to reach USD 6.54 trillion in 2022 [2]. The share of global online commerce in total commerce is at 16% in 2020 and is expected to reach 22% by 2023 [3]. Worldwide, the scale of spending on digital media advertising was USD 355 billion in 2020 and is likely to grow to USD 460 billion in 2024, with at least a quarter of this spend made on social media marketing [4].

India being one of the most populous countries in the world is among the fastest growing e-commerce markets with GMV expected to surpass USD 200 billion by 2026. Internet users are expected to increase from 687.62 million in 2019 to 829 million by 2021. The country's internet penetration rate grew from just 4% in 2007 to 52.08% in 2019, registering a compound annual growth rate of 24% between 2007 and 2019 [5].

With the evolution of this new medium for businesses, early market researchers suggested that a user visits online platforms to purchase goods and services under two segments: search-based and experience-based [6]. In both segments, end-user engagement is an important factor for culminating in online transactions and its efficacy depends not only on the attributes and technologies of the digital platform but also on individual preferences [7], which may vary based on the dominant traits of an individual's personality [8].

Socio-psychological factors that deeply influence acceptance and adoption of computing technologies have seen significant research work focused on the technology adoption model (TAM), which had breakthrough observations on empirical factors that drive the use of a new system [9]. Research in the area of human psychology has formulated a widely accepted Big 5 personality traits model for an individual [10]. This model is reasonably universal in its ability to define individual behaviors; however, research on the impact of these traits on digital platform adoption is limited.

With the rising relevance of digital technologies, substantial research has been conducted in the past two decades on their impact on UI, Design and Features, which enables marketers to make effective pitch [11]. Broadly, research studies focused on the evolution of technology platforms for ecommerce, social networking, mobile apps etc including elements such as design thinking methods, content handling, offerings, and user interface and experience, primarily to create and improve user engagement, and increase the chances of completing transactions [12].

Given the scale of digital usage growth in India coupled with government's push for digital transformation [13], the country's complex social and cultural demography provides an interesting background to study the relationship, if any, between digital quotient and individual behavior, which may be relevant to digital adoption. An exploratory study for this market was conducted on the premise that new user traits, outside the Big Five personality traits, may have emerged with the adoption of emerging digital platforms, and they may also have a major effect on users' online engagement models. The proposed research attempts to identify key personality traits associated with an individual's digital quotient. This study also contributes to the literature on digital quotients by providing a theoretical framework of key personality traits taxonomy. These were identified through an initial qualitative survey and by applying principles of natural language processing (NLP) to find the most relevant words that exhibit proximity to a high digital quotient.

Further research on the evolving strong relationship between personality traits and the digital quotient may help marketers and technology players design better user engagement of the platform and eventually promote their online offerings [8]. If we make qualified progress in this area, then the findings may help to assess personalization driven marketing—reinforcing the established concept of "market of one" [14].

2. Literature Review

A rigorous review of previous literature was conducted covering areas such as electronic commerce, social media and commerce, TAM, theory of reasoned action (TRA), Big 5 personality traits, design thinking, and emerging technologies leveraging digital platforms.

The largest interface between an individual and emerging digital technologies is in the space of online commerce (e-commerce, s-commerce, or m-commerce). While e-commerce growth has challenged traditional sales channels, a study [15] observed that the relationship between physical local channels and internet-based channels was critical for the emergence and overall growth of e-commerce. This study also argues that real-world behaviors are the baseline for an evolving online world and this relationship cannot be ignored.

Socio-economic factors such as wealth, beliefs, culture, income groups, and social connections influence users' buying behavior in the early days. Once users become accustomed to digital buying, the impact is minimal and does not create a differentiated impact [16]. The key demographic factors are age and education, which influence purchase intentions in a social commerce setting [17]. In rural areas, where internet access is a prized possession, economic, social, and psychological factors are important for effectively engaging consumers on digital platforms [18]. In e-commerce, consumer buying depends on influencing factors such as financial savings, information availability, and convenience of buying [19]. Among the financial factors, it is observed that deep discounting offered on online platforms drives positive online buying behaviors. This discounting, when coupled with the convenience of transacting online, has a much better impact than discounting alone [20].

Human behavioral factors are closely associated with predictors of online buying behavior, while it is observed that two factors—information gathering and perceived convenience—have the most influence [21]. Related to information gathering, about 70% of purchasers engage in collecting information from social media sites, and in 49% of cases, buying decisions were influenced by this information. Two-thirds of buyers agreed that recommendations they receive online from other online users are valuable, credible, and influence their perception of a brand and influence their purchase decision [22]. A study on the credibility valuation of messaging communicated via digital platforms concluded that the informative value of influencer-generated content, and the influencer's trustworthiness, attractiveness, and similarity to followers positively affect follower's trust in influencer's branded posts, which subsequently influence brand awareness and purchase intentions [23].

In web-based commerce, perceived convenience [21] enables users to differentiate between good and bad purchases based on the perceived control and pleasure they experience toward their planned purchases, and both factors can effectively improve the chances of a repeat consumer (i.e., consumers returning to a website) [24]. Additionally, users generally engage more on digital platforms if they are seeking search-based goods/services rather than experience-based goods [25]. Consumers use value-added search as a factor that may influence unplanned purchases [24]. In digital platform adoption, non-rational assessment factors such as perceived playfulness and individuals' habits significantly impact users' continuance intention to frequent and transact than perceived usefulness. To attract users, website designers should be aware of users' aesthetics and hedonic needs [11].

This study also referred to the Big 5 model for assessing personality traits such as openness, conscientiousness, extraversion, agreeableness, and neuroticism (OCEAN). Extraversion, which is the most dominant characteristic, influences an end user's participation in online social networks [7]. The other traits relevant to an individual's use of social networking platforms are neuroticism, openness to experience, agreeableness, and conscientiousness, although they are less dominant in their effect [3]. The phenomenon of impulse buying on online channels has three elemental traits: agreeableness, need for arousal, and need for material. These traits are coupled with value consciousness, which has a mediating effect and is negatively associated with the dependent variable [26]. While investigating the influence of personality traits on financial decision making among younger generations, Nga and Yien [8] find that conscientiousness, openness, and agreeableness have a significant influence on risk aversion, cognitive biases, and socially responsible investing, respectively.

The influence of both external (i.e., marketing, promotions, critiques) and internal factors (i.e., word of mouth, social communication) assist to make online product offerings acceptable to end users [27]. Engagement with social media brand communities leads to a positive increase in purchase expenditures [28]. The results were more positive when they were able to find additional information on relevant products fairly quickly [29]. Extending the understanding on consumers' brand-related activities, Senthil et al. [30] indicate that consumers show higher believability in how a brand and product information is shared on online social platforms.

In online communities, aspects that impact usage include content of discussions, diversity, frequency, quality of interaction, levels of commitment, interpersonal perceptions, reciprocity and complementarity, power and conflict, self-disclosure, and levels of satisfaction reported in community relationships [31]. A deeper analysis of social media data and users' digital footprints (online cues) show that the accuracy of usage prediction is consistent across the Big Five personality traits, and accuracy improves when the analysis includes input data of demographics and multiple types of digital footprints across features [32].

The five key behavioral attributes influencing customer engagement in social commerce (s-commerce) platforms are social, motivational, technological, moderator, and outcomes [33]. In social commerce induced transactions, users are guided by the perceived credibility of the information that eventually influences relationship-orientation, which plays a significant role in inducing consumer engagement [12]. An end user's openness to experience emerged as a significant trait that has an indirect effect on social commerce adoption intentions [17].

An exploratory study conducted on the similarity between virtual avatar-based end-user engagements observed that online profile factors make a difference in low-involvement purchase conditions, whereas the traditional sales criterion makes a bigger difference in high-involvement purchase conditions [34]. Studies show that end users tend to customize their mobile applications, which predict an individual's personality traits, and this indicates that end-user patronage directly correlates with personality traits [35]. An interesting aspect of the perceived social image of a user is observed following the adoption of smart wearable devices that significantly accelerated buying decisions [36].

A study assessing differentiating parameters among genders elucidated that emotion, trust, and convenience are three key determinants that separate women from men in online shopping behavior [37]. Risk aversion or mitigation is a key socio-psychological factor that influences online engagement on digital platforms, although it may vary between genders [38]. A study conducted on the transition from traditional banking to online platforms finds that psychological factors such as perception of relative advantage, compatibility, trial ability, and perceived risk about the internet influence end user's intentions to adopt internet banking services [39].

The stickiness of the cognitive design of a digital platform ensures higher consumer engagement and improves the chances of making a purchasing transaction. The stickiness may be due to designing for effective usage of technologies toward engagement or usability of the site from the perspective of user behavior [40]. There are two main cognitive response level drivers of emerging technology acceptance at an individual's perception level: perceived usefulness (PU) and perceived ease of usage (PEOU) [41]. PU refers to the belief that the target digital platform will help users accomplish their objectives, whereas PEOU relates to the belief that the platform would be easy to use and free of physical or mental effort. Additionally, the studies observed that PU can accelerate the use of PEOU for the same user. In addition, another relevant factor that complements TAM is the perceived enjoyment (PE), referring to the extent to which the activity of using the digital platform brings in hedonic benefits [42].

Influencers that may impact the adoption of digital platforms by end users may vary depending on the user's space. Users who are more aligned to the home environment have a natural drift toward PE as a key driver, whereas users who spend more time in the workplace will prefer to adopt PU [43]. Both PE and PEOU correlate strongly with hedonic environments and significantly influence user's intention to use digital platforms [42]. Recent research on mobile internet usage reveals that both PEOU and PE have surpassed PU on end user's online shopping intentions [44]. Further research signifies the addition of various factors such as subjective norms, task characteristics, individual and cultural differences, and workplace environmental factors to the basics of the TAM model. Meta-analysis studies applying TAM to a variety of technologies have confirmed that it may explain the underlying rationale for adoption and usage of online services [45, 46].

A study done on health industry in Jakarta observed that digital quotient, authentic leadership, and perceived organizational support together present stronger influence work engagement of the employees. [54]. Strong leadership leverages employees of high digital quotient to improve use of technologies in the organization [55].

3. Research Gaps

The rigorous literature review has helped in identifying that research has occurred at a reasonably significant scale over the past two decades. The findings of various studies provide qualified relevance to the design language, features, and offers on online digital platforms, which has further enabled better end-user adoption. Aligned with the fast-paced emergence of digital technologies, further research has been conducted on the design and feature enrichment of digital platforms and its impact on users' experience level, thus making it work better on the key elements of the TAM (usefulness, ease of use, and enjoyment).

Research on human psychological factors in emerging digitalized societies and the associated personality traits that are closely associated with digital platform adoption has been explored by leveraging the Big 5 trait model and TRA, and segmented correlations have been found between traits and individual behaviors on digital platforms.

Neural networks based deep machine learning for unsupervised analysis is an area which is actively researched recently. In terms of natural language programming, visual inputs adds to output quality as multimodal data can increase the mutual information between source and translation. [47] The neural networks model have an innate nature of decaying memory of input compared to output generated from RNN (recurrent neural networks). The add-ons of scaling factors in the RNN model to adaptively adjust memory led to advanced model of extended long short term memory (ELSTM) and dependent bidirectional recurrent neural networks (DBRNN) with better relational output. [48] Tree structured multi linear principal component analysis (TMPCA) is able to facilitate sequence-based text classification tasks by preserving strong mutual information between its input and output mathematically [49] The text dimension reduction methods normally use the word-level inputs, whereas the TMPCA method reduces the dimension of input sentences & simplify the text classification tasks [50] Text representation is based upon text mining techniques which is fundamental to intelligent information retrieval & processing using two tasks: indexing and weighting. [52].

Such studies in the space of personality traits and their impact on the adoption of digital platforms were conducted using quantitative analysis of past research and largely leveraged one or many of these Big 5 personality traits as starting points. Thus, recent research studies may show potential bias toward the five traits, even though a potential exists that new behaviors or traits may have emerged due to the surge in socio-psychological changes in societies, largely impacted by the rapidly evolving digital space.

The recent accelerated digitalization of socio-economic models and merging of millennial and generation Y provide a reasonable push to rediscover these traits. A possibility cannot be ruled out that while the Big 5 personality traits—conceptualized during the 1960s and 1980s when digital was not even coined—are still relevant in the new digital society, new traits have been added to this array. Therefore, an opportunity exists to study end user's behaviors ab-initio and identify the key drivers of their responsiveness toward digital platforms.

This exploratory study intends to augment or complement previous research by conducting a primary survey with participant inclusive research. Further to the findings of this study, the analysis includes theoretical correlation with the Big 5 personality traits by identifying the commonalities and differences, if any.

4. Research Methodology

A. Research Design

The study applied a descriptive, exploratory, qualitative approach conducting online telephonic surveys in two phases between March and June 2019 and March and June 2020 across geographic clusters in India. Furthermore, the analysis and interpretation were conducted by leveraging some of the contemporary methods and technologies in NLP.

B. Sampling

The target sample for primary research was generated through three layers of sampling techniques to remove biases and yet retain good feasibility for rich data collection. The following techniques were used in stages to filter the target samples.

- Stage 1: The geographic cluster sampling technique helped to identify three metro cities in India which have the highest internet penetration and data consumption rate through telecom network access [53].
- Stage 2: A stratified sampling technique helped to identify the target respondents through demographic spread based on six filter criteria of digital technology exposure, even distribution of income slabs, frequent social media usage, smartphone usage, e-commerce exposure, and good interactive communication. The three differentiated segments of sources were identified, which showed a good probability of finding respondents with more than six filter criteria. The three sources identified were college-goers, working class people, and families in residential societies. An initial list of 385 possible respondents was created after gathering random data through primary contacts at these three sources. An outreach to this sample of 385 people helped in drawing a qualified (six filter criteria as above) target population of 153 respondents.
- Stage 3: The initial contact was made verbally through references to explain the purpose and inclu-

sivity in the survey. The convenience sampling technique was eventually leveraged to seek respondents who agreed to the primary survey requirements of two stages across the research period. The shortlisted 153 respondents were approached for participating in the Stage 3 level of the survey, and 112 agreed to participate in the survey. Eventually, 83 actively responded to Stage 1 of the survey and 42 from the same sample actively responded to Stage 2. This generated a 95% confidence level and a +10 confidence interval, which was acceptable given that we had a representative population size of over 7 million and the responses were qualitative.

The survey was conducted in two phases:

- Part 1: (April–June 2019): An open-ended questionnaire through online/computer-assisted telephonic mode was followed by in-depth interviews to help clarify the responses. The initial findings were shared with the respondents.
- Part 2: (April–June 2020): Validation of the initial findings of Part 1 through a slider-scale-based survey.

C. Data Collection

The data were collected in two parts as detailed below. Part 1 of the survey was exploratory in nature and was conducted using a simple structured subjective open-ended questionnaire asking respondents to provide their views in a descriptive format. The respondents were asked a total of 10 questions focusing on awareness, responsiveness, and adoption. The responses were in the form of words/phrases/sentences that best represented their views on the question. Each question could have responses ranging from more than one word to a phrase. The respondents were encouraged to complete their response within 10 minutes to capture their initial perspective. The mode of response was through an internet survey and/or a computer-assisted telephonic survey.

In instances where the user's response was limited and needed further understanding, an in-depth interview was conducted to explore more intensive responses.

The questionnaire was created around 10 clusters based on the highlights of the literature reviews, and each cluster represented a specific category under which a digital quotient was observed. The respondents were asked to freely state their views on the question asked under that cluster. The clusters are as shown in Table I:

TABLE I. LIST OF KEY CLUSTERS ENCOMPASSING VARIOUS FACTORS COVERED IN THE LITERATURE REVIEW ON THE SUBJECT

SI. No	Cluster Type	Description
1	Demographic	Meta data of a user such as age, gender, location, employment, and marital status.
2	Socio-economic	Socio-economic factors such as wealth, beliefs, culture, income group, social connections, friends and family, and social order/cohesion/stability.
3	Physiological	Individual perceptions, behaviors, attitude, motivation, experiences, and thought patterns.
4	Social behavior	Interactions among individuals toward coexistence, collaboration, and competition to survive situations.
5	Platform features alignment	Evolution of features on digital platforms and how they create engagement with human behaviors. The premise is to gather factors that generate an active response from a user.
6	Information influx	A user's ability to gather and process information and intent to leverage it in their life.
7	User education	A user's education and skills status and its impact on digital quotient.
8	Peer pressure	A user's association with peers and factors influencing the user's digital quotient.
9	Virtual profile	Evolving stature of an individual building a virtual profile on digital media that may display significantly different attributes than the existing physical profile. Generally seen as the release of suppressed desires/wishes.
10	Workspace	Association with a professional work environment and its influence on the user's digital quotient.

A total of 83 respondents provided narrative answers that consisted of 853 content words and phrases (representing key behavioral descriptions), after eliminating the stop words and delimiters. These data were used for text mining and analytics to make further conclusions. The findings of Part 1 of the survey were shared with them along with their original responses.

Part 2 consisted of a conclusive survey after a gap of 12 months and was conducted with a follow-up online telephonic survey. The second survey was conducted after a year with the same target set of 83 respondents and was organized to provide for some time lapse. This helped to assess if the initial findings of the traits survived over a reasonable lapse of time. The respondents were requested to provide their answers on a slider scale of 0 to 100% on their agreement with the findings of Part 1.

Note 1: Part 1 findings were concluded in the form of seven traits and a suggested framework, and are detailed in the analysis section.

Note 2: The researcher did not contact the respondents for almost a year to avoid influencing their opinion on the subject.

D. Ethical Considerations

All participants were informed about the study purpose and consented (verbally) to participate in the survey.

5. DATA ANALYSIS AND INTERPRETATION

The responses were gathered in the format of documents from respondents against each question. The various algorithms assessed to conduct text extraction to identify most relevant words were Latent Semantic Analysis (LSA), Exploratory Factor Analysis (EFA), Relevant Score Analysis (RSA) and Term Frequency-Inverse Term Frequency (TF-IDF). Since the respondents data was not measured against any scale; the best suited method identified were related to text extraction methods used in the NLP supporting tools to identify the most relevant words among the texts gathered in the survey. The two different algorithms were used so that any biases could be identified and moderated, thus providing more objective results. These algorithms were RSA and TF-IDF as both are established tools used in machine learning automation frameworks by leading cloud service providers like Facebook, Google in rank ordering a particular word for a specificity. The section 2 and 3 provide the details on these algorithm used in this research. Section 1 deals with cleansing of the base dataset.

a) SECTION 1: Bag of words: Removal of stop words and delimiters from the text collated from the respondents. These stand for often repeated words but are mere fillers/binders between the content words (bag of words, also called content words). Example Stop words = [is, not, that, there, are, can, would, may he, she, you, with, of, those, after, all, one] and Delimiters = [.,,]

b) SECTION 2: Word frequency cluster wise and relevance score based on collocation in text responses: No occurrences of the content words in the text gathered in every cluster, as stated in Table I (after eliminating stop words and delimiters). Shortlist all content words based on a cutoff frequency of 2%. Build & Rank based upon a relevance score value for each word based on its association, at large, with other words in the text-based responses.

c) SECTION 3: Term Frequency–Inverse Document Frequency (TF–IDF) score: The association of a word with a high frequency in a), along with the occurrence of other words making it more relevant and, therefore, more useful than just having a higher frequency but independent standing. The term frequency and IDF is leveraged to identify the significance of a keyword across all 83 responses. The input for calculating the TF–IDF was the keywords identified with high frequency in a).

SECTION 1: This section shares information on the demographic characteristics of the 83 respondents (Table II).

The youngest respondent was 19 years of age and the oldest was of 55 years of age. The average age was 37.1 years, median was 40 years, and standard deviation was 8.9. Overall, 83 respondents participated in full and provided qualified responses. A total of 853 words/phrases were identified after eliminating all stop words and delimiters. These words were studied further as stated in the Section 2, as follows.

SECTION 2: Analysis using keyword frequency (number of occurrences) in every cluster and relevance score collocation with each keyword.

TABLE II. DEMOGRAPHIC CHARACTERISTICS OF THE RESPONDENTS (83)

Category	Frequency	Percentage
Gender		
Male	60	72%
Female	23	28%
Age Group		
Below 30	24	28%
Between 30-40	30	36%
Above 40	29	34%
Education		
Technical	42	51%
Non-technical	41	49%
Graduate	49	59%
Postgraduate	34	41%
Working status		
Working full time	66	79%
Working part time	17	21%
Marital status		
Married	69	83%
Unmarried	14	17%
Financial status		
Average earning pa	35.8 lacs INR	NA
Median	35.5 lacs INR	NA
Standard deviation	21.32	NA

A total of 853 content words were allocated against each cluster based on their origin (Table I) and after applying the word frequency as a differentiator (Section 1), the content words were identified with a high frequency of occurrence. The word frequency helped in selecting keywords that were most frequently used by respondents in each cluster. Words ranked as the top five or six were shortlisted against each cluster with minimum 2% as frequency cut off. Figure 1 displays the frequency occurrence across all the ten clusters for each of the content words shortlisted in each cluster.

Figure 1. Word Cloud of Keywords

Each content word was associated with its relevance score in the text collected from the respondents in each cluster. The relevance score was calculated based on the following formula:

$$Function\,(RS) = \left(\frac{\beta}{\mu}\right) \quad (1)$$

where, RS: relevance score
α = independent term frequency (occurrence as an independent word – let's say the target word). (It is calculated as sum total count of number of times a target word appears in the sample data)
β = associated term frequency (all combinations where the keyword was collocated with other keywords thus highlighting the association between the target word & other words). (It is calculated as sum total count of number of time the target word is observed being used concurrently with another word so as to make a qualified statement)
$\mu = \alpha + \beta$ = Total content words collected in the bag of words for the cluster. This provides the total universe of words where the target word exists – either independent or associatively.

Both the 'α' and the 'β' have an independent and random occurrences in responses. If the 'β' is higher and 'α' is lower, it tends to highlight the associative nature of the word. If 'β' is lower and the 'α' is higher, it tends to highlight the independent nature of the word. If 'β' and 'α' are equal in occurrences, then the RS will be 0.5. Thus the range of the RS is between 0 and 1.

Relevance score provides a moderation of the uniqueness of the content word. This helps wherever a content word is frequently used along with other keywords, thus associating a higher relevance to the stated keyword. This is used in priority ranking of the keywords during the final analysis. The higher the RS value, more relevant is the word due to its higher associative occurrences compared to independent occurrences. Wherever a keyword was associated with more than one cluster, the parameters were considered as aggregated values for many clusters.

Table III provides an analysis of the content words with

a) Occurrence frequency (>2%) among the respondents as per the question asked in the questionnaire.
b) RS calculated for these words (see the formulae as above)

SECTION 3: Analysis and extraction of keywords TF–IDF methodology. The TF–IDF methodology was used to extract keywords that are most frequently used by respondents across all clusters. Thus, words with the highest frequency from Table II were identified overall with a relevance score. The relevance is the factor that reflects the occurrence of a word in conjunction with other words while conferring the end purpose. Thus, the higher the relevance of a word, the more significant it becomes as a keyword.

TF–IDF denotes term frequency and inverse term frequency. This numerical statistical method calculates the importance of a keyword in a document by covering two important factors [53].

Term frequency (TF) suggests how many times (frequently) a word occurs in all the documents as a ratio with all the words in the documents.

$$Term\ Frequency\,(t) = \left(\frac{number\ of\ times\ t\ appears\ in\ a\ document}{total\ number\ of\ terms\ in\ the\ document}\right) \quad (2)$$

Note: We considered 38 words identified in Section 2.

Inverse document frequency (IDF) indicates the chances of occurrence of a term across multiple documents. It is calculated as the logarithm of the ratio of the number of documents in the survey divided by the number of documents where the specific term appears. It is calculated as

$$IDF\,(t) = \left(\frac{Total\ number\ of\ documents}{Number\ of\ documents\ with\ t\ in\ it}\right) \quad (3)$$

Term frequency–inverse reverse frequency (TF–IDF) is the multiplication of the above two resultants. It is calculated as follows:

$$TF - IDF = Term\ Frequency\,(t) \times IDF\,(t) \quad (4)$$

Note: We considered a total of 83 documents in the study as individual documents per respondent. The 57 words with a high frequency of occurrence were searched in each of these 83 documents to calculate the TF–IDF.

Table IV lists all the keywords as shortlisted in the word cloud in Figure 1 along with their TF–IDF rating score.

Tables V and VI present a comparative list of all the keywords with respect to the ranking order of their TF–IDF and relevance score. The intent was to identify the top 20 ranked keywords in both categories and to explore which keywords matter almost simultaneously.

Table V represents keywords with TF–IDF as the first field sorted from the highest value to the lowest. Table VI represents keywords with Relevance Score as the first field sorted from highest to lowest.

The 17 keywords of the 20 given in the list were identified as common in both tables and occur simultaneously as keywords.

A comparison between the two tables involved using different methods to avoid any bias in the shortlisting for final conclusions.

The observations and interpretation in the study, including the keywords analysis, helped the researcher conclude the following personality traits as key differentiators. The description states the responsive behavior against the stated

traits as covered in the survey results.

Table VII enlists major keywords that are common in both analysis into finer and smaller groups without losing effectiveness. (-) denotes that the word is to be seen as a negative connotation. The top 20 key words as shortlisted in the table VI were compiled into subgroups based upon similar behavior; however authors used their discretion in opting one word from the subgroup as a title which sums up and conveys the prime behavior. Thus the column three in the table VII represents the seven words as title for the group (signifying the trait).

Table VIII provides a theoretical taxonomic framework (UCCCEEE [updated, confident, connected, curious, experimentative, efficient, and epicurean] Framework) adopted by the author to effectively communicate the findings and recall. This framework organizes and explains the personality traits of an individual that have a significant influence on the adoption of digital platforms.

6. VALIDATION OF FRAMEWORK

The validation was sought from the original participants on the findings of seven traits identified as UCCCEEE framework post the initial survey conducted and after significant period of a year had passed to provide for any change in outlook as well.. They were asked to share their alignment to the relevance of the seven traits identified in the study as key influencers on digital quotient. The respondents were also asked to provide their rating score on the positive influence of these traits on a rider scale of 0 (least influence) to 100 (very high influence). A total of 69 individuals eventually responded until this paper being written/revised. Table V shows the analysis of this validation survey.

Table IX presents the findings of the validation survey conducted by the researcher using the same sample set, of which 69 responded. The slider scale was used, and the test had an acceptable reliability score (Cronbach's alpha = 0.81).

A comparison drawn between the validation Table IX and Table VI reveal some interesting relationship. All 07 traits had some mapping with the top 10 traits identified having high scores of TF-IDF and RS. The highest trait was "Updated" in Table IX and was observed as 2nd highest score in Table VI with "Knowledge" ranked as 11th position. The trait "Confident" was lowest in Table IX and was ranked in Table VI as 17^{th} with Fear of Change (-) as 20^{th}. The other traits were reasonably interspersed in the ranking orders of both tables.

The high average score on the rating scale from the participants during validation cycle suggested the seven traits represents high influence on the digital quotient. The findings in the table V, VI and IX all closely associated the seven traits as having significant influencers.

Analysis was also conducted to draw a comparison between the Big 5 personality traits of individuals and the UCCCEEE framework. The findings draw interesting parallels between the five traits of the personality model toward human behavior and the seven traits based on the UCCCEEE framework for digital quotient.

Table X provides a theoretical comparison between the traits identified in the Big 5 psychological model and the seven traits in the UCCCEEE framework.

This analysis concludes that although the study was conducted at the ab-initio level and without any initial biases to any standing theories, it draws some similarities with the five traits of the Big 5 model.

A significant conclusion may be made regarding the two traits that are completely new and do not have any parallel with the Big 5 traits. These are Updated and Epicurean. It is likely that these two traits may have emerged due to the power of digitalization toward the information and content revolution in our lifestyles. The trait Updated denotes that while we are inundated with an influx of information flow, which is made easy due to the internet, the individual's needs, wants, and desires have also grown to stay updated. The possibility of receiving more information flow has created a habitual expectation to seek more information and its influence on behavior and decision making are greater than before. Similarly, content driven entertainment has seen multifold growth as it becomes easy to generate and distribute content with ease of usage and consumption. This has also influenced individuals to unabashedly feed their hedonistic behaviors and eventually propel Epicurean as an important and fast evolving trait that influences an individual's digital platform adoption.

7. Conclusion & Further Research

The research findings reveal that an individual's digital quotient is relational to a set of key behaviors that are differentiated and propelled by key personality traits. The study, therefore, proposes that certain personality traits summarize a set of these key behaviors. These personality traits are identified as a theoretical taxonomic framework abbreviated as UCCCEEE.

The authors believe that the most influencing trait is *Updated*, reflecting that digital adoption is led by the information revolution and users' propensity to gather information and data at a scale and reach that was not possible without a digital medium. The *Updated* trait has been well leveraged by the marketing & advertisement agencies to provide for adequate information on the online channels so as to generate informed decision making. This helps build confidence and conviction in the users to stay engaged on the digital platform for making purchases. The trait of *Curiosity* refers intensity of the urge an individual has

TABLE III. BAG OF WORDS AND RELEVANCE SCORE FOR KEYWORDS

Sr. No	Question Cluster (Bag of words)	**Word Frequency** (NOTE: Words having a higher frequency of occurrence were preferably shortlisted. It was also observed that as we went to frequency equivalent to 4% or below, the words with a singular or a few occurrences appeared thus making them gradually irrelevant. In a few cases, 2% was allowed just to consider words at boundary level. The approach in two such clusters was to consider inclusivity for maximum words as far as possible unless the word frequency was rendered closer to 1). These two clusters were *SOCIAL BEHAVIOR CLUSTER* and *INFORMATION INFLUX CLUSTER*.					
Q1	*Which key demographic factors largely make a differentiating impact on an individual becoming digitally active and comfortable? (Demographic factors include but are not limited to age group, gender.)*						
	Demographic Cluster (172)	Age	Gender	Education	Language	Income	Accessibility
	Frequency	36	14	13	07	13	08
	%	20.9%	8.1%	7.5%	4.0%	7.5%	4.6%
	Relevance score	0.547	0.341	0.266	0.354	0.261	0.238
Q2	*What type of impact does a person's economic status have on his/her becoming comfortable with the digital environment?*						
	Socio-Economic Cluster (50)	Affordability	Impactful	FOMO	Economic	NA	NA
	Frequency	23	4	3	2		
	Percentage	46.0%	8.0%	6.0%	4.0%		
	Relevance score	0.595	0.061	0.652	0.056		
Q3	*Identify the key mindset barriers a person faces while he/she begins to adopt a digital media environment.*						
	Psychological Cluster (82)	Fear of change	Privacy	Ease of use	Security	NA	NA
	Frequency	25	8	10	17		
	Percentage	30.4%	9.7%	12.2%	20.7%		
	Relevance score	0.638	0.525	0.972	0.467		
Q4	*Identify the social behaviors that have a significant influence on a person adopting a digital media environment.*						
	Social Behavior Cluster (77)	FOMO	Networking	Influence	Updated	Experimentative	Ambitious
	Frequency	7	19	11	21	4	2
	Percentage	9.0%	24.6%	14.3%	27.3%	5.2%	2.6%
	Relevance Score	0.652	0.946	0.516	0.961	0.761	0.112
Q5	*Which top characteristics of a digital platform would make it very attractive to a user?*						
	Platform Feature Alignment Cluster (120)	Ease of use	Relevance	Popularity	Personalization	Features	Security
	Frequency	54	16	10	26	07	08
	Percentage	45.0%	13.3%	8.3%	21.6%	5.8%	6.6%
	Relevance Score	0.972	0.521	0.191	0.695	0.117	0.517
Q6	*What type of information inflow influences a person and makes him/her more digitally savvy?*						
	Information Influx Cluster (75)	Socialization	News	Trending	Updated	Convenience	Chatting
	Frequency	15	7	12	24	2	7
	Percentage	20.0%	9.3%	16.0%	32.0%	2.6%	9.3%
	Relevance Score	0.828	0.509	0.641	0.961	0.862	0.298
Q7	*What type of skills or education makes a person more open and adoptive of digital media?*						
	User Education Cluster (67)	Curiosity	Education	Innovation	Reasoning	Language	Technology
	Frequency	12	7	6	5	16	8
	Percentage	17.9%	10.4%	8.9%	7.4%	23.8%	11.9%
	Relevance Score	0.708	0.266	0.515	0.156	0.354	0.132
Q8	*What would impress you most among your peers who are digitally savvy?*						
	Peer Pressure Cluster (68)	Updated	Efficient	Connected	Confident	Knowledge	Popular
	Frequency	17	12	4	5	6	4
	Percentage	25.0%	17.64%	5.8%	7.4%	8.8%	5.8%
	Relevance Score	0.961	0.306	0.906	0.656	0.608	0.791
Q9	*How does an individual's behavior vary from the physical world to the digital world? Or, is it the same?*						
	Virtual Profile Cluster (67)	Alter Profile	Frankness	Virtual Avatar	Expressions	Adventurous	Touch feel
	Frequency	17	10	19	11	3	4
	Percentage	25.3%	14.9%	28.3%	16.4%	4.4%	5.9%
	Relevance Score	0.682	0.481	0.689	0.262	0.708	0.061
Q10	*Does the workplace make you digitally more active or your home influence? Which attributes play a key role at either place?*						
	Workspace Cluster (121)	Influence	Efficient	Networking	Learning	Happiness	Entertainment
	Frequency	34	14	13	10	08	16
	Percentage	28%	11.5%	10.7%	8.2%	6.6%	13.2%
	Relevance Score	0.516	0.706	0.946	0.204	0.732	0.903

TABLE IV. BAG OF WORDS AND TF–ID RATING SCORE FOR THESE KEYWORDS

SN	Keyword	TF–IDF
1	Ease of use	0.2594
2	FOMO	0.2526
3	Fear of change	0.2023
4	Alter profile	0.1981
5	Efficient	0.1957
6	Confident	0.1942
7	Popular	0.1893
8	Virtual Avatar	0.1882
9	Experimentative	0.1584
10	Age	0.1549
11	Personalization	0.1547
12	Entertainment	0.1525
13	Updated	0.152
14	Trending	0.1486
15	Happiness	0.1442
16	Connected	0.1366
17	Socialization	0.1327
18	Networking	0.1317
19	Security	0.1237
20	Language	0.1164
21	Affordability	0.1052
22	Impactful	0.0891
23	News	0.0783
24	Innovation	0.0748
25	Learning	0.0715
26	Influence	0.071
27	Relevance	0.0699
28	Expressions	0.0636
29	Knowledge	0.063
30	Reasoning	0.0626
31	Frankness	0.0578
32	Gender	0.0453
33	Education	0.0446
34	Chatting	0.0412
35	Privacy	0.0378
36	Adventurous	0.0376
37	Technology	0.0341
38	Education	0.0337
39	Income	0.0305
40	Accessibility	0.0267
41	Features	0.022
42	Touch feel	0.0209
43	Convenience	0.0153
44	Ambitious	0.0114
45	Economic	0.0091

TABLE V. KEYWORDS WITH RANKING ORDER OF TF–IDF AND FOLLOWED BY RELEVANCE SCORE

SN	Keyword	TF–IDF	Relevance Score
1	Ease of use	0.2594	0.972
2	FOMO	0.2526	0.652
3	Fear of change	0.2023	0.638
4	Alter profile	0.1981	0.682
5	Efficient	0.1957	0.706
6	Confident	0.1942	0.656
7	Popular	0.1893	0.791
8	Virtual avatar	0.1882	0.689
9	Experimentative	0.1584	0.761
10	Age	0.1549	0.547
11	Personalization	0.1547	0.695
12	Entertainment	0.1525	0.903
13	Updated	0.152	0.961
14	Trending	0.1486	0.641
15	Happiness	0.1442	0.732
16	Connected	0.1366	0.906
17	Socialization	0.1327	0.828
18	Networking	0.1317	0.946
19	Security	0.1237	0.517
20	Language	0.1164	0.354

TABLE VI. KEYWORDS WITH RANKING ORDER OF RELEVANCE SCORE AND FOLLOWED BY TF-IDF RATING SCORE FOR THESE KEYWORDS

SN	Keyword	TF–IDF	Relevance Score
1	Ease of use	0.2594	0.972
2	Updated	0.152	0.961
3	Networking	0.1317	0.946
4	Connected	0.1366	0.906
5	Entertainment	0.1525	0.903
6	Convenience	0.0153	0.862
7	Socialization	0.1327	0.828
8	Popular	0.1893	0.791
9	Experimentative	0.1584	0.761
10	Happiness	0.1442	0.732
11	Knowledge	0.063	0.708
12	Adventurous	0.0376	0.708
13	Efficient	0.1957	0.706
14	Personalization	0.1547	0.695
15	Virtual avatar	0.1882	0.689
16	Alter profile	0.1981	0.682
17	Confident	0.1942	0.656
18	FOMO	0.2526	0.652
19	Trending	0.1486	0.641
20	Fear of change	0.2023	0.638

to seek/know more and this trait goes well with surge in the search engine driven economy. Users with higher curiosity stay for longer hours on the internet searching for additional information, increasing their engagement time & thus providing a good ROI for digital platforms as longer eye balls generates higher chances of converting into sales. *Experimentative* signifies that users who are comfortable to experiment with new things / experiences, are more open to accelerated diversifying & evolving digital platforms as they provide a sense of excitement and natural satisfaction to them. This makes it conducive place for such users to come and hang around eventually making them a relevant economic entity for digital platforms. *Confident* as a trait has many ways to reflect upon. Firstly the risks of the digital medium are still at an early stage of evolution thus reflecting lesser hesitance toward adoption. Secondly the users seems to be more open and willing to experiment and thus self-confidence accentuates this behavior. Thirdly the benefits from the digital platform is pushing users to trade off risks or hasten up through learning curves associated with these platforms. The younger generation does not consider *Confident* as a necessary attribute as they do not have to shift from an old baseline to a new one and it holds no more a threshold value before the usage begins. Connected is an attribute which accentuates socialization behavior over networking platforms. Some users aggressively position themselves on such platform to highlight a to and fro impact factor on engagement using peer influence. Social commerce identifies *connected* trait as key driver of engagement. *Efficient* trait signifies that benefits user may see in leveraging the digital technologies. However wider penetration of digitalization is yet to arrive in personal lives beyond socio-economic models. Respondents rated hedonistic needs and wants as the drivers of early adoption of the digital OTT medium thus making *Epicurean* trait as catalyst towards rich quality of streaming content based transformation of the entertainment industry.

TABLE VII. KEYWORDS WITH HIGH TF–IDF AND RELEVANCE SCORES AND ARRANGED IN GROUPS WITH SIMILAR HUMAN BEHAVIORS

Keywords	**Prime behaviors reflected in these keywords**	**Personality attributes as proposed in the study**	**Taxonomy Framework for the outcome**
Fear of missing out (FOMO) (-)	Eagerness to know more; proactively reaches out	Curious	UCCCEEE (Updated, Curious, Confident, Connected, Experimentative, Efficient, Epicurean)
Ease of use; efficient; personalization; Convenience	Clarity of thoughts and choices; seeks productivity in work and lifestyle; leverages digital to make better and finer choices	Efficient	
Confident; fear of change (-)	Resilience against fear of unknown or change; makes confident and clear choices; at peace with self	Confident	
Networking; socialization; popular; trending; connected	Extroversion; driven by need to stay connected in social space; driven by mass recognition	Connected	
Updated; Knowledge	Information gatherer; has eye for detail and feels comfortable even during information overflow	Updated	
Alter profile; virtual avatar; experimentative	To break repetitiveness and explore unchartered space; highly imaginative and takes chances; easily explores digital for new things	Experimentative	
Happiness; entertainment	Hedonistic gratification; content driven	Epicurean	

TABLE VIII. THEORETICAL TAXONOMIC FRAMEWORK OF SEVEN PERSONALITY TRAITS HAVING SIGNIFICANT INFLUENCE ON INDIVIDUAL DIGITAL QUOTIENT

Sl. No	**Attribute type**	**Description**
1	Updated	Information gatherer, has eye for detail, and feels comfortable in information overflow
2	Curious	Eagerness to know more, proactive reach out, insightful, analytic, and inquisitive about a subject
3	Confident	Resilience against fear of the unknown or change, makes confident and clear choices, at peace with self, and ability and willingness to trade off with the unknown ahead
4	Connected	Extroversion, driven by need to stay connected in social spaces, and driven by mass recognition
5	Experimentative	To break repetitiveness and explore unchartered space, highly imaginative and takes chances, explores digital for new things, enthusiastic about new ideas, and willing to approach/adopt them
6	Efficient	Clarity of thought and choices, seeks productivity in work and lifestyle, leverages digital to make better and finer choices, and productivity driven on time and efforts
7	Epicurean	Driven by hedonistic drivers such as self-pleasure/entertainment and content driven

TABLE IX. KEYWORDS WITH RANKING ORDER OF RELEVANCE SCORE AND FOLLOWED BY TF-IDF RATING SCORE FOR THESE KEYWORDS

Survey Cronbach's Alpha Score	0.81		
Target Participants	83 (same as those who took the first test) Responded: 77		
Attribute	**Average Score**	**Min Score***	**Max Score***
Updated	88.6	45	97
Curious	84.4	41	97
Confident	73.9	04	95
Connected	83.2	25	96
Experimentative	75.2	38	98
Efficient	71.6	03	95
Epicurean	86.6	35	98

**score of 100 and 0 are replaced by the nearest score*

TABLE X. CCCEEE FRAMEWORK BASED SEVEN TRAITS AND COMPARISON BETWEEN OCEAN MODEL (BIG 5 PERSONALITY TRAITS)

Sl. No	**Trait as per UCCCEEE framework**	**As per Big 5 Personality Trait (OCEAN) model**	**Remarks**
1	Updated	-	No correlation found
2	Curious	Openness	Direct correlation—those who are high on openness may have a higher digital quotient
3	Confident	Neuroticism	Inverse correlation—those who are low on neuroticism may have a higher digital quotient
4	Connected	Extraversion	Direct correlation—those who are high on extraversion may have a higher digital quotient owing to their social comfort and associations
5	Experimentative	Openness	Direct correlation—those who are high on openness may have higher digital quotient as they may be prone to experimentation
6	Efficient	Conscientiousness	Direct correlation—those who are high on conscientiousness may a have higher digital quotient owing to their focus on efficiency
7	Epicurean	-	No correlation found

The literature review also highlighted that socio-economic, demographic, psychological, behaviors, tech specifications, information flow, systems user interface, workplace models, social peer pressure, hedonistic content, and characteristics are some attributes that influence individuals' awareness, responsiveness, and adoption of digital transformation. Theoretical comparison with the well-established Big 5 personality trait theory confirms that these traits are still relevant in the digital space. However, the two traits that have gained significance and bring in a distinct presence over and above the big 5 traits are Updated and Epicurean. Thus, the UCCCEEE framework provides a more comprehensive and contemporary coverage of all personality traits and redefines them in the pursuance of the digital transformation journey. The proposed taxonomic framework simplifies the research findings into an easy and relatable model for individuals to assess their strength and weakness as the eco system around them continues to undergo a skill disruption through the route of digital transformation. To human capital managers at organizations, this may help in redefining the jobs and roles specs and mapping talent acquisition and retention strategies accordingly. The marketers and sales leaders in the organization may leverage this to define propensity models for lead conversions and identify better ways to engage target individuals on digital media. State governance and societies at large can take benefit from further research in this area as it may help them build societal characters preparing well towards the digital economy.

This paper considered the basic definition of Digital Quotient as *"Response generated by an individual against a stimulus sent on any digital media"*. Given the vast expanse of the topic and still it being an evolving space, eventually the generally accepted definition of an individual's DQ may not be limited to the above. This exploratory study was confined to a few metro cities in India. Further studies on wider socio–economic-geographic scale by including rural areas may establish the higher reliability of this framework. Globally, digital transformation is happening at an overwhelming rate, and the reliability/consistency of this framework across the longitudinal timeline needs to be studied. A focused study toward defining an individual's profile based on the UCCCEEE framework & the correlational relationships between these profiles and online transactions may help marketers understand and identify better and fruitful targets. The research acknowledges that 42 respondents validation of the UCCCEEE framework may have limitations on conclusions, however the respondents had to be from the original sample size making it more relevant for assessment. A future consideration of larger sample size may bring sharper correlations between Table VI and Table IX. As the researchers have adopted convenience sampling, the findings of the study may have limited generalizability.

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References

[1] Internet World Stats. https://www.internetworldstats.com/stats.htm

[2] Statista, "Retail e-commerce sales worldwide from 2014 to 2023(in billion U.S. dollars)." https://www.statista.com/statistics/379046/worldwide-retail-e-commerce-sales/

[3] Smart Insights, "Forecast growth in percentage of online retail / Ecommerce sales 2017 to 2023." https://www.smartinsights.com/digital-marketing-strategy/online-retail-sales-growth

[4] Statista, "Digital advertising." https://www.statista.com/outlook/216/100/digital-advertising/worldwide#market-revenue

[5] India Brand Equity Foundation, "E-commerce Industry in India." https://www.ibef.org/industry/ecommerce.aspx

[6] R.A. Peterson, S. Balasubramanian, and B. J. Bronnenberg, "Exploring the implications of the internet for consumer marketing," J. Acad. Mark. Sci., no. 329, September 1997.

[7] S. Gosling, A. Augustine, S. Vazire, N. Holtzman, and S. Gaddis, "Manifestations of personality in online social networks: self-reported Facebook- related behaviors and observable profile information," Cyberpsychol. Behav. Soc. Netw., vol. 14, no. 9, pp. 483–88, September 2011.

[8] J. K. H. Nga and L. K. Yien, "The influence of personality traits and demographics on financial decision making among generation Y," Young Consumers, ISSN: 1747–3616, August 2013.

[9] F.D. Davis, R. P. Bagozzi, and P.R. Warshaw, "User acceptance of computer technology: a comparison of two theoretical models," Manage Sci., vol. 35, no. 8, August 1989. https://doi.org/10.1287/mnsc.35.8.982

[10] S.V. Paunonen and M.C. Ashton, "Big Five factors and facets and the prediction of behavior," J. Per. Soc. Psychol. vol. 81(3), pp. 524–539, 2001. https://doi.org/10.1037/0022-3514.81.3.524

[11] C. Liao, P. L. To, C.C. Liu, P.Y. Kuo, and S.H. Chuang, "Factors influencing the intended use of web portals," Online Inf. Rev., vol. 35(2), pp. 237–254, April 2011.

[12] W. H. S. Tsai and L. R. Men, "Motivations and antecedents of consumer engagement with brand pages on social networking sites," J. Interact. Advert., vol. 13(2), pp. 76–87, September 2013.

[13] Digital India. www.digitalindia.gov.in

[14] M. Wedel and W. A. Kamakura, "Introduction to the special issue on market segmentation," Intern. J. Res. Mark., vol. 19, pp. 181–183, 2002.

[15] M. Gabrielsson and P. Gabrielsson, "Internet-based sales channel strategies of born global firms," Int. Bus. Rev., vol. 20, no. 1, pp 88–99, February 2011.

[16] B. Hernández, J. Jiménez, M. J. Martín, "Age, gender and income: do they really moderate online shopping behavior?" Online Inf. Rev., vol. 35, no. 1, pp. 113–133, February 2011.

[17] G. Aydin, "Do personality traits and shopping motivations affect social commerce adoption intentions? Evidence from an emerging market," J. Internet Commer., vol. 18, no. 4, pp. 428–467, September 2019. https://doi.org/10.1080/15332861.2019.1668659

[18] N. Balakrishnan, "Factors influencing the buying behavior of rural consumer through online in Karur district," RJCBS, vol. 07, no. 06, April 2018.

[19] A. Alexiou, D. Riddlesden and A. Singleton, "The geography of online retail behaviour," in Consumer Data Research, P. Longley, J. Cheshire, and A. Singleton, Eds. UCL Press, 2018, pp. 96–109. https://www.jstor.org/stable/j.ctvqhsn6.10

[20] S. Saranya and S. Poongodi, "Consumers' buying behavior towards online shopping – an empirical study in Bangalore city," TIJ's Res. J. Commer. Behav. Sci., vol. 05, no. 02, December 2015.

[21] S. Bellman, G. L. Lohse, and E. J. Johnson, "Predictors of online buying behavior," Commun. of the ACM, vol. 42, no. 12, December 1999.

[22] DEI Worldwide, "The impact of social media on purchasing behavior," vol. 1: Initial findings, United States 2008. http://www.deiworldwide.com/files/DEIStudy-Engaging%20ConsumersOnlineSummary.pdf

[23] C. Lou and S. Yuan, "Influencer marketing: how message value and credibility affect consumer trust of branded content on social media," J. of Interact. Advert., vol. 19, no. 1, pp. 58-73, February 2019. https://doi.org/10.1080/15252019.2018.1533501

[24] M. Koufaris, A. Kambil, and P. A. LaBarbera, "Consumer behavior in web-based commerce: an empirical study," Int. J. Electron. Commer., vol. 6, no. 2, pp. 115–138, December 2014. https://doi.org/10.1080/10864415.2001.11044233

[25] K.P. Chiang and R. R. Dholakia , "Factors driving consumer intention to shop online: an empirical investigation," J. Consum. Psychol., vol. 13(1&2), pp. 177–183, 2003. https://doi.org/10.1207/S15327663JCP13-1&2_1

[26] W. H. S. Tsai and L. R. Men, "Motivations and antecedents of consumer engagement with brand pages on social networking sites," J. Interact. Advert., vol. 13(2), pp. 76–87, September 2013.

[27] C. Dellarocas, X. M. Zhang, and N. F. Awad, "Exploring the value of online product reviews in forecasting sales: The case of motion pictures," J. Interact. Mark., vol. 21(4), pp. 23–45, 2007. https://doi.org/10.1002/dir.20087

[28] K.-Y. Goh, C.-S. Heng, and Z. Lin, "Social media brand community and consumer behavior: quantifying the relative impact of user- and marketer-generated content," Inf. Syst. Res., vol. 24 (1), pp 88–107, March 2013. https://doi.org/10.1287/isre.1120.0469

[29] D.G. Muntinga, M. Moorman, and E.G. Smit, "Introducing COBRAs: exploring motivations for brand-related social media use," Int. J. Advert., vol. 30, no. 1, pp. 13–46, January 2015. https://doi.org/10.2501/IJA-30-1-013-046

[30] M. Senthil, N. R. V. Prabhu, and S. Bhuvaneswari, "Customers' perception towards advertising in the online shopping and social networking websites among internet users in India," AIJM, vol. 2, no. 1, pp. 50–59, 2013.

[31] N. Hair, M. Clark, and M. Shapiro, "Toward a classification system of relational activity in consumer electronic communities: The moderators' tale," J. Relatsh. Mark. Vol. 9(1), pp. 54–65, March 2010. https://doi.org/10.1080/15332660903552238

[32] D. Azucar, D. Marengo, and M. Settanni, "Predicting the Big 5 personality traits from digital footprints on social media: A meta-analysis," Elsevier, vol. 124, pp. 150–159, April 2018.

[33] A. H. Busalim, A. R. C. Hussin, and N. A. Iahad, "Factors influencing customer engagement in social commerce websites: a systematic literature review," J. Theor. Appl. Electron. Commer. Res., vol. 14, no. 2, 2019. http://dx.doi.org/10.4067/S0718-18762019000200102

[34] I. Pentina and D.G. Taylor, "Exploring source effects for online sales outcomes: the role of avatar buyer similarity," J. Custom. Behav., vol 9. no. 2, pp. 135–150, 2010. https://doi.org/10.1362/147539210X511344

[35] R. Xu, R. M. Frey, E. Fleisch, and A. Ilic, "Understanding the impact of personality traits on mobile app adoption – insights from a large-scale field study," Comput. Human Behav., vol. 62, pp. 244–256, September 2016.

[36] A. Adapa, F. F. H. Nah, R. H. Hall, K. Siau, and S. N. Smith, "Factors influencing the adoption of smart wearable devices," Hum-comput. Interact., vol. 34, no. 5, pp. 399–409, 2018. https://doi.org/10.1080/10447318.2017.1357902

[37] S. Rodgers and M.A. Harris, "Gender and e-commerce: an exploratory study," J. Advert. Res., vol. 43, no. 3, pp. 322–329, September 2003.

[38] J. Sinha, "Factors affecting online shopping behavior of Indian consumers," University of South Carolina, 2010.

[39] M. Tan and T. S. H. Teo, "Factors influencing the adoption of internet banking," J. Assoc. Inf. Syst., vol. 1, no. 5, July 2000.

[40] V. Venkatesh and R. Agarwal, "Turning visitors into customers: a usability-centric perspective on purchase behavior in electronic channels," Manage. Sci., vol. 52, no. 3, pp. 367–382, March 2006. ISSN 0025-19091 EISSN 1526- 55011061520310367

[41] F.D. Davis, "Perceived usefulness, perceived ease of use, and user acceptance of information technology," MIS Q., vol. 13, no. 3, pp. 319–340, September 1989.

[42] H. Van der Heijden, "User acceptance of hedonic information systems," MIS Q., vol. 28, no. 4, pp. 695–704, December 2004.

[43] Aharony, 2014

[44] U. Cheema, M. Rizwan, R, Jalal, F. Durrani, and N. Sohail, "The trend of online shopping in 21st century: impact of enjoyment in TAM model," Department of Management Sciences, The Islamia University of Bahawalpur, Pakistan, Asian Journal of Empirical Research, vol 3, No 2, pp.131-141, 2013.

[45] Q. Ma and L. Liu, "The technology acceptance model: a meta-analysis of empirical findings," J. Organ. End User Comput., vol. 16, no. 1, pp. 59–72, 2004.

[46] S. Yousafzai, G. Foxall, and J. Pallister, "Technology acceptance: a meta-analysis of the TAM," J. Model. Manage., vol. 2, no. 3, pp. 251–80, November 2007.

[47] Y. Su, K. Fan, N. Bach, C.-C.J. Kuo, and F. Huang, "Unsupervised multi modal neural machine transaltion," 2019. https://arxiv.org/abs/1811.11365

[48] Y. Su and C.-C.J. Kuo, "On Extended Long Short-term Memory and Dependent Bidirectional Recurrent Neural Network" Neuro Computing vol. 356 no.2019, pp. 151–161, September 2019. https://doi.org/10.1016/j.neucom.2019.04.044

[49] Y. Su, Y. Huang and C.-C.J. Kuo, "Efficient Text Classification Using Tree Structured Multi Linear Principal Component Analysis," 24th International Conference on Pattern Recognition (ICPR), 2018, pp. 585–590, https://doi.org/10.1109/ICPR.2018.8545832

[50] Y. Su, R. Lin and C.-C.J. Kuo, "Tree-structured multi-stage principal component analysis (TMPCA): Theory and Applications, Expert Sys Appl, vol. 118, pp. 355–364, March 2019. https://doi.org/10.1016/j.eswa.2018.10.020

[51] W. Zhang, T. Yoshida and X. Tang, "A comparative study of TF*IDF, LSI and multi-words for text classification," Expert systems with Applications, vol. 38 no. 3, pp. 2758–2765. March 2011. https://doi.org/10.1016/j.eswa.2010.08.066

[52] T. O'Gara, "NLP and Initial Word Vectorization" February 2020. https://medium.com/@thomaslowell21/nlp-and-initial-word-vectorization-c0d6e3a25bae

[53] Data15, www.dot.gov.in, 2018.

[54] Adellia Anggun Trisnawati , Kerin Sianto, Lady Aldli Sansyah, Nopriadi Saputra, Jurnal Akuntansi, Kuangun, dan manajemen, ISSN 2716-0807, Vol 2, No 4, 2021, 255-278, 2021. https://doi.org/10.35912/jakman.v2i4.425

[55] Ririn Fitaloka, Bima Sugarai, Andi Randirga Arung Perkasa, Nopriadi Saputra; Leadership Agility and Digital Quotient Influence on Employee Engagement: A case of PT X and Pinrumah.com; DOI: 10.21512/tw.v21i2.6768; E-ISSN 2541-2388; September 2020.

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