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A Data Mining Approach for Analyzing Personality, Cognitive and Emotional Features of Social Network Consumers

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Abstract:- The current research examines the personality characteristics and emotional intelligence of young adult consumers who shop through social media. Consumer behaviour has long piqued the research community's curiosity. Contemporary customer behavior analysis considers a wide variety of influences affecting the consumer and recognizes a wide variety of buying behaviors other than shopping. Due to the fact that online sales are now an everyday occurrence, it is beneficial to research online customers who are social media users who shop via social media. Personality traits and emotional characteristics, as described in emotional intelligence, are two critical components that affect consumer behaviour. Emotional intelligence is a component of personality and intellectual ability that is inherited by one's parents and grows - develops over one's lifespan. The term "personality" refers to the pattern of emotions, feelings, and actions that distinguishes individuals from one another. These have an effect on how an individual thinks, feels, and behaves against itself and others.

The results were gathered by having participants complete the self-report questionnaire Trait Emotional Intelligence (TEIQue) for emotional intelligence and Eysenck Personality Questionnaire (EPQ) for personality characteristics associated with personality disorders. The collected data were then chosen for review, undergoing necessary transformations to ensure that they were in a format appropriate for implementation of the respective machine learning algorithms provided in the R Software.

Additionally, the appropriate set of algorithm parameters was calculated based on the implementation scenario in order to generate inference rules. Several algorithms were introduced in response to particular research concerns, including classification algorithms for the generation of decision trees based on the four more general factors of emotional intelligence (welfare, self-control, emotionality, and sociability), as well as personality characteristics of social network users. Following a weighting and criterion-based analysis, the findings obtained present consumers' ratings, which are used to determine the degree of emotional intelligence and personality traits. Personality and emotional intelligence indices may be critical in elucidating social network users' consumer behaviour.

Keywords:- *Consumer Behaviour, Emotional Intelligence, Personality, Data Mining.*

I. INTRODUCTION

Contemporary consumer behaviour analysis considers a wide variety of influences affecting the consumer and recognizes a wide variety of buying behaviors other than shopping. Personality and emotional intelligence are two critical components that affect customer behaviour. The term "personality" refers to the pattern of emotions, feelings, and actions that distinguishes individuals from one another. These have an effect on how an individual thinks, feels, and behaves against itself and others (*Cohen et al., 2008*). Emotional intelligence (EI) can be characterized as the capacity to track one's own and others' emotions, to distinguish between and properly mark various emotions, and to use emotional knowledge to direct one's thought and behaviour (*Engel et al., 1995*). Trait EI is described as "a set of emotional self-perceptions at the base of personality." Trait EI, in layman's words, refers to an individual's self-perceptions of his or her emotional capacity (*Wilson, 2019*).

1.1. Eysenck Personality Questionnaire (EPQ)

Numerous hypotheses about personality have been suggested. Several of these have already been listed in so-called "theories of traits." Allport, Guilford, Cattell, and Eysenck have all developed those. There are distinct hypotheses that share a similar trait: the factorial study of the personality's qualities and attributes, which are derived from an individual's behaviour (*Revelle, 1995*). This is the spirit in which Eysenck's principle operates. It evolved from a comparison of Kant's personality characteristics to Wundt's four idiosyncrasies and system dimensions, as well as certain aspects of Galen's theory, and can be schematically expressed as follows:

Eysenck's 1947 diagram distinguished two fundamental aspects of personality, defined by two intersecting axes (Figure 1). The maximum and minimum values of the dimension Eysenck dubbed "Emotionality or Instability or Neuroticism" were set at the vertical axis's two poles. The highest value indicated the presence of

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instabilities, such as neuroticism, while the lowest indicated the presence of mental maturity. On the horizontal axis, the other component of personality, Inwardness - Extraversion, was plotted. As for the vertical axis, the highest value denoted the extroverted personality traits, while the opposite pole, the lowest value, denoted the introverted personality traits (*Eysenck, 1950; Eysenck & Eysenck, 1968*).

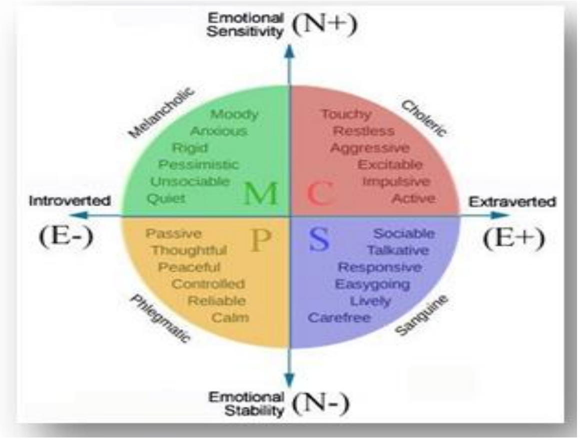

Figure 1: EPQ Dimensions

Eysenck's personality measurements are distinct categories of individuals, each with a unique collection of characteristics traceable back to their behaviors and reactions. What is proposed is the identification of an individual's unique reactions, which would provide proof of his typical reactions and therefore of his typical behaviour. This enables assumptions to be made on some aspects of his personality. These characteristics are regarded as the components of each of the three dimensions of personality (types). Because of the association between the reactions and their normal presence, they serve as valid guidelines for ascribing specific attributes to a person's personality. That is, measurements or forms of personality are concepts that include a set of similar traits that we deduce from the individual's reactions and behaviour.

1.1.1.Description of psychometric scale EPQ

In depth, the three suggested personality measurements are as follows:

Introversion vs. extraversion: Extroverts are outgoing, enjoy group activities, have a large social circle, and dislike reading and learning. Additionally, has a strong appetite for emotion, seizes chances, enjoys risk, responds quickly, and is usually impulsive. The traditional introvert is calm, isolated, intuitive, likes books written by others, is restrained and keeps a distance from all but very close friends, does not like strong emotions, takes daily issues seriously and prefers a well-planned life, manages his emotions, is trustworthy, cynical, and places a high premium on moral principles. Extroverted and introverted people behave and believe differently.

Neurotism - Instability – Emotional Stability: Neurotism refers to an individual's general mental instability, emotional hyperactivity, and proclivity to exhibit neurotic symptoms in response to stress. Individuals with elevated neurotic beliefs are nervous, depressed, and often depressed. When neurotism is combined with a high level of extroversion, the person becomes irritable, anxious, and sometimes violent. On the other hand, low prices indicate an emotionally stable individual with moderate reactions and a relatively stable system of beliefs, attitudes, and behaviour.

Psychoticism: This component referred to the third personality factor, "Psychotism" (P), which also encompasses subjective personality characteristics. This predisposition occurs to varying degrees in all people, and only its extremely high importance can be indicative of psychosis.

As a consequence of these findings, a measurement scale for the three dimensions of personality (E, N, and P) was created, as well as a complementary dimension of the L that quantifies the falsehood of the responses provided by the individual questioned during the questionnaire. The Eysenck pair introduced a new scale in 1975, dubbed the Eysenck Personality Questionnaire (E.P.Q.) (*Cooper & Petrides, 2010*).

1.2. Trait Emotional Intelligence (EI)

The TEIQue is based on a psychological paradigm that incorporates the construct into prevalent differential psychology models. It covers all 15 dimensions of the trait EI sampling domain. Numerous independent tests have established that the TEIQue is substantially more accurate at predicting parameters (outcomes) than other questionnaires (*Mikolajczak & Roy, 2007*).

The TEIQue in its entirety possesses outstanding psychometric properties. It has been used in a variety of experiments where it was necessary to determine adaptive facets of personality. That include neuroscience, interpersonal wellbeing, psychopathology, addictions, response time, and overall health, as well as behavioral genetics (*Halkiopoulos et al., 2020a*).

The TEIQue operationalizes Petrides and colleagues' model of EI as a personality trait. The evaluation consists of fifteen subscales classified according to four dimensions: well-being, self-control, emotionality, and sociability.

Figure 2: TEIQue Aspects

1.2.1.Description of psychometric scale EI

The Well-being aspect is composed of three distinct characteristics: Happiness, Optimism, and Self-esteem. They assess people's perceptions of their overall level of life satisfaction. The term "well-being" refers to people's views of how cheerful and comfortable they are on a regular basis, their optimism for the future, and their self-esteem.

The Self-control dimension quantifies the extent to which individuals believe they can control or are influenced by their urges. It is composed of three distinct personality characteristics: Impulse Control, Stress Management, and Emotional Regulation.

Emotionality consists of four distinct characteristics: Empathy, Emotion Perception, Emotion Expression, and Relationships. They together indicate your level of awareness of your own emotions and feelings, as well as the emotions and feelings of others. The scores on these characteristics indicate how much you appreciate this 'emotional literacy,' as well as where and how you use it. Self-aware individuals who manage their emotions appropriately react compassionately to the emotions and thoughts of others at the appropriate time.

Sociability refers to how at ease people feel in a variety of social situations, from celebrations and social events to formal business meetings. By completing the test, you indicated your level of confidence in communicating with a variety of different types of individuals, your belief in your ability to persuade others, and your comfort level with making your case. The Sociability factor is a composite of the characteristics of Emotional Control, Assertiveness, and Social Awareness (*Petrides & Furnham, 2006;2003*).

II. METHODOLOGY

Machine learning and data mining techniques were used in this article to determine the personality dimensions (EPQ) and emotional intelligence quotient (TEIQue) of social network consumers. The method is composed of three distinct measures. The first stage was to create electronic questionnaires and distribute them through the website http://www.cicos.gr. Following that, data was collected and preprocessed from the questionnaires. The data set for analysis included demographic details about respondents, such as their ethnicity, birthplace, and current residence, as well as educational records for both respondents and their parents, as well as professional occupations for their parents. The third stage involved reviewing the data collected and assessing the results using Data Mining techniques. More specifically, we used classification algorithms to uncover hidden patterns in the results. Decision trees are an important representation and interpretation method for psychological statements. They are made up of consecutive decisions with varying results that occur over a given time span.

2.1 Decision-Making in Consumer Behavior

The role of mood and personality characteristics in decision-making has been explored in foreign literature (*Gohm and Clore, 2002; Luce, 1998*). The aim of the study is to thoroughly comprehend how consumers use behavioral data to improve decision based on their personality traits. A increasing body of research focuses on the emotions that consumers experience through purchases; moreover, a greater understanding of emotional cognitive ability may have a substantial impact on consumer success outcomes. The current study focuses on emotional intelligence, personality traits, and consumer behavior in young adults who use digital platforms.

Consumer emotional intelligence is described as an individual 's ability to use complex knowledge to achieve a desired consumer outcome. It is composed of a set of first-order emotional abilities that allow individuals to comprehend the meanings of emotional patterns that underpin consumer decision-making, as well as reason and solve problems based on them (*Mayer and Salovey 1997*). A better perception of dynamic capability can be highly beneficial in raising consumer perception of their actions. It will discuss, for example, how emotional reasoning influences purchase decisions, which decisions are more readily taken by consumers with a high versus a low EI, and how EI may influence relationships between key consumer variables such as impulsivity and purchasing intention. Using this knowledge about emotional ability, we will also be able to identify consumers who make the highest (and lowest) quality buying decisions. For example, consumers who have a high level of nutritional knowledge but lack the emotional capacity to distinguish between appropriate and inappropriate emotions and to regulate their emotions around unhealthy food are more likely to make poor quality decisions (*Gkintoni et al., 2016*). Understanding these emotional deficits may help to increase the consistency of subsequent consumption decisions (*Halkiopoulos et al., 2020b*).

Recent advances in personality science can estimate consumer motivation in terms of the impact of personality characteristics on consumer behaviour. Traits are enduring and consistent patterns of actions, perceptions, and emotions that differ between people. Researchers have traditionally been interested in learning how people vary, but they've spent a lot of time figuring out how to quantify, chart, and classify personality traits (*Togias et al., 2015*). Trait theory was used to try to figure out what personality characteristics people have. According to trait approach, personality is made up of quantifiable, observable qualities or units called traits. Traits are predispositional characteristics that are somewhat permanent (*McLeod, 2014*). A personality has its own set of characteristics, and considering their consistency, individuals with a particular set of characteristics should be assumed to behave predictably in different contexts and over time (*Udo-Imeh et al., 2015*).

Researchers are rethinking what characteristics are and where they come from, seeing attributes as long-term motivators that guide their decision-making. Personality characteristics, for example, have been attributed to a variety of outcomes, including experiential purchasing tendencies, political affiliation, natural language adoption, pet preferences, the status of one's personal living environment, and even more significant life outcomes including divorce, morbidity, and professional attainment. According to some new research, people who find themselves in disease-infested areas are less accessible and extraverted, possibly because they are less willing to learn and engage with others, lowering their risk of being sick (*Weller et al., 2018*).

2.2 Data Mining Techniques

Data mining is a relatively new method of knowledge exploration that involves retrieving previously undiscovered, actionable information from large science and commercial databases. It is compelled by the exponential growth of such databases. Typically, a data mining technique derives rules from complex categorical and/or numerical data. The most well-known data mining techniques are classification, clustering, and association. Classification is a widely used data mining task. Classification seeks to extract knowledge that can be used to categorize data into predefined classes, each of which is characterized by a collection of attributes. Numerous schemas may be used to describe the extracted knowledge. The most well-known of these schemas are decision trees, "if-then" rules, and neural networks (*Tan et al., 2006*).

III. RESULTS

Classification techniques are used to distinguish groups based on certain distinguishing characteristics. They derive value from a variety of human behaviors, most notably automatic decision-making. Decision trees are an extremely successful supervised learning technique. Its objective is to partition a dataset into classes that are as homogeneous as possible in terms of the expected component. It accepts a series of classified data as input and produces a tree resembling an orientation diagram, with each leaf representing a judgment (a class) and each non-final node (internal) representing a test. Each leaf reflects the decision to belong to a particular level of data by validating the direction taken by all tests from the root to the leaf. The tree is more concise, because it seems to be simple to use theoretically. It's more interesting to obtain a tree that has been tuned to the probabilities of the variables under test. The tree that is largely balanced would be a positive outcome. If a sub-tree can only lead to a single answer, then the whole tree can be simplified to a single simple conclusion; this simplifies the mechanism without affecting the final outcome. Ross Quinlan was involved in the creation of this kind of decision tree.

Decision trees are constructed using a series of training data or data sets as "ctree (Conditional Inference Trees)." At each node of the tree, "ctee" selects one attribute of the data that most efficiently divides the sample array into subsets enriched in one or more classes. Its criterion is the normalized knowledge gain (difference in entropy) associated with the selection of an attribute for data splitting. The decision is made using the attribute with the highest normalized knowledge gain. It is possible to handle data during the decision tree's creation. Certain attributes have an undefined value when the benefit or gain ratio for that attribute is evaluated using only the documents for which it is specified. By calculating the probability of different results, it is possible to distinguish documents of uncertain values using a decision tree. Ctree, like ID3 or C4.5, constructs decision trees from a collection of training data using the principle of knowledge entropy.

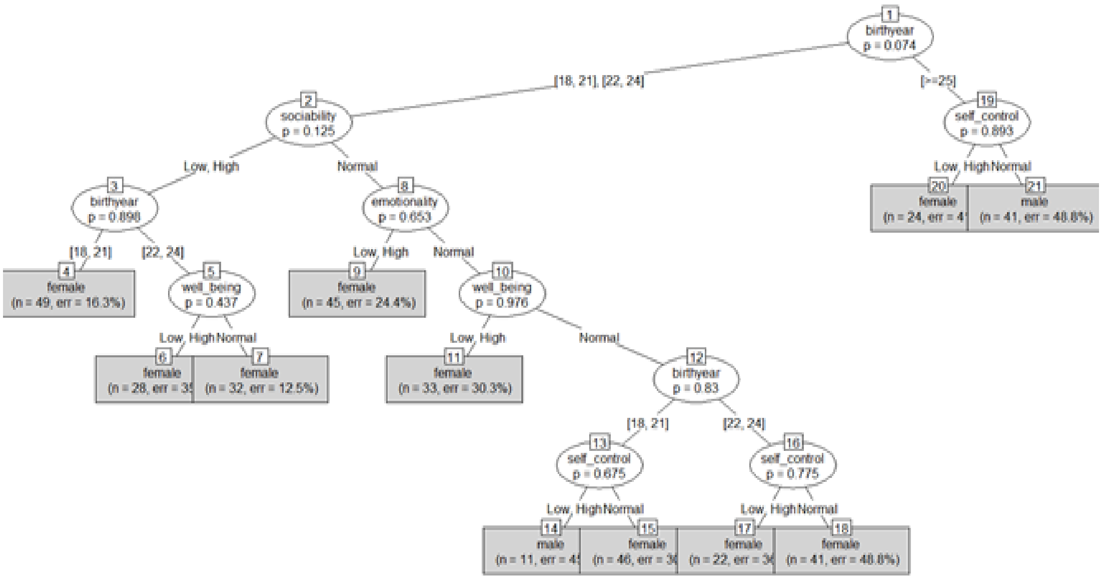

Figure 3: Decision Tree I

The training data is a set $S = s_1, s_2, \dots$ of already classified samples. Each sample s_i consists of a p-dimensional vector $(x_{1,i}, x_{2,i}, \dots, x_{p,i})$, where the x_j represent attribute values or features of the sample, as well as the class in which s_i falls. At each node of the tree, "ctree" selects the data attribute that most efficiently divides the set of samples into subsets enriched of one or more classes. The criterion for splitting is the gain in normalized information (difference in entropy).

The decision is made using the attribute with the highest normalized knowledge gain. After that, the "ctree" algorithm is repeated on the smaller sublists. To obtain the optimal result, it was important to better integrate the data into the model. This mission was accomplished by modifying and checking the "ctree" keys.

Tree I (Figure 3)

- ✓ Depended variable: birthyear
- ✓ Independed variables: sex, well_being, sociability, emotionality, self_control

Tree II (Figure 4)

- ✓ Depended variable: birthyear
- ✓ Independed variables: Rest

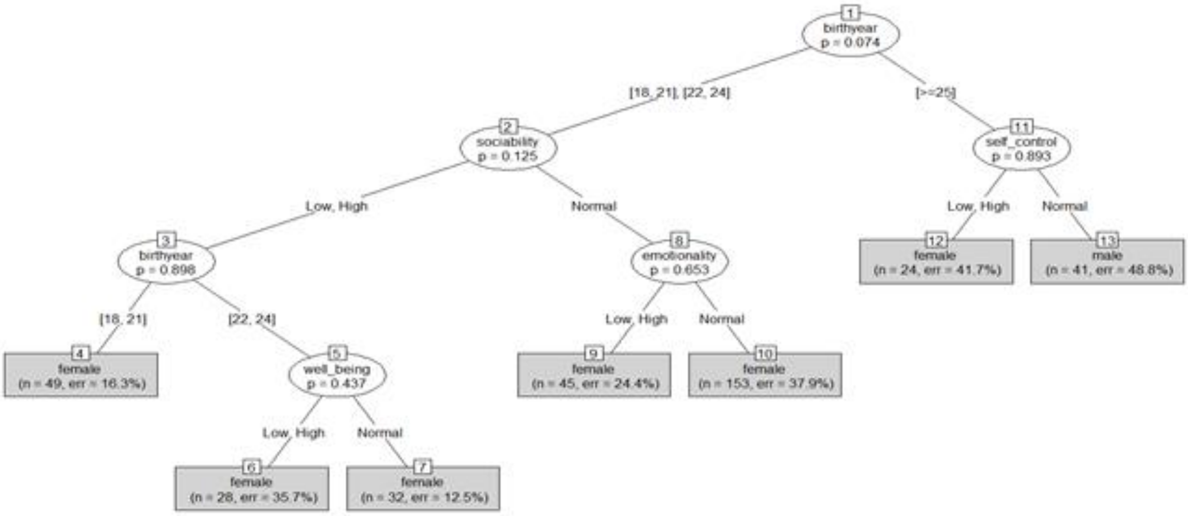

Figure 4: Decision Tree II

3.1 Mining Association Rules

Association Rule Mining is a widely used method for discovering relations between a large number of variables. Apriori is a well-known algorithm for learning association rules in Data Mining. Apriori is intended to be used for applications that contain transactions (for example, data collected from surveys in this case). As is customary in association rule mining, given a set of item sets, the algorithm seeks out subsets that are familiar to at least a minimum C of the item sets (*Maimon & Rokach, 2010*).

Apriori takes a "bottom-up" approach, extending periodic subsets one thing at a time and testing classes of candidates against the data. When no further successful extensions are discovered, the algorithm terminates. Apriori effectively counts candidate item sets using breadth-first search and a tree structure. It produces candidate item sets of length k from length k 1 item sets. Then it eliminates applicants from an uncommon subpattern. The candidate set includes all frequent k-length item sets, as described by the downward closure lemma. Following that, it queries the transaction database to ascertain the most frequently occurring item sets among the applicants (*Tan et al., 2006*).

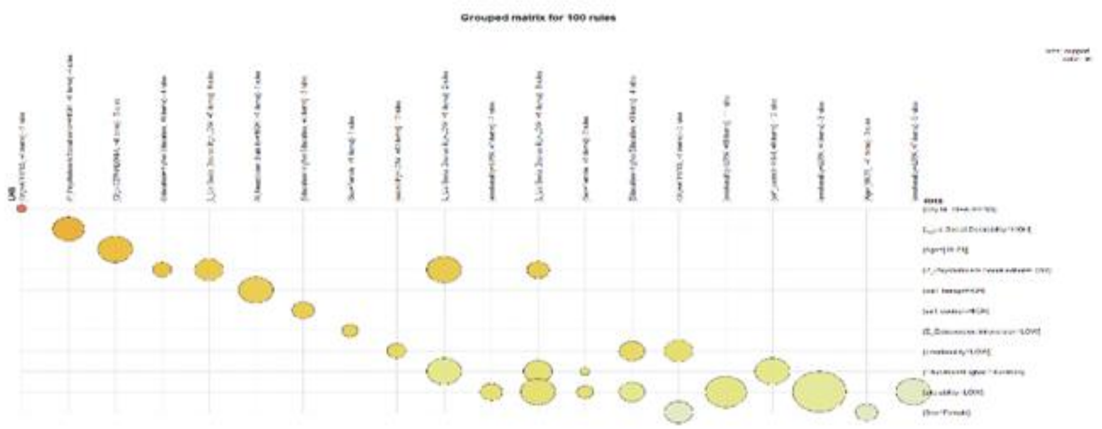

Figure 5: Grouped Matrix Plot

3.2 Apriori rules visualization

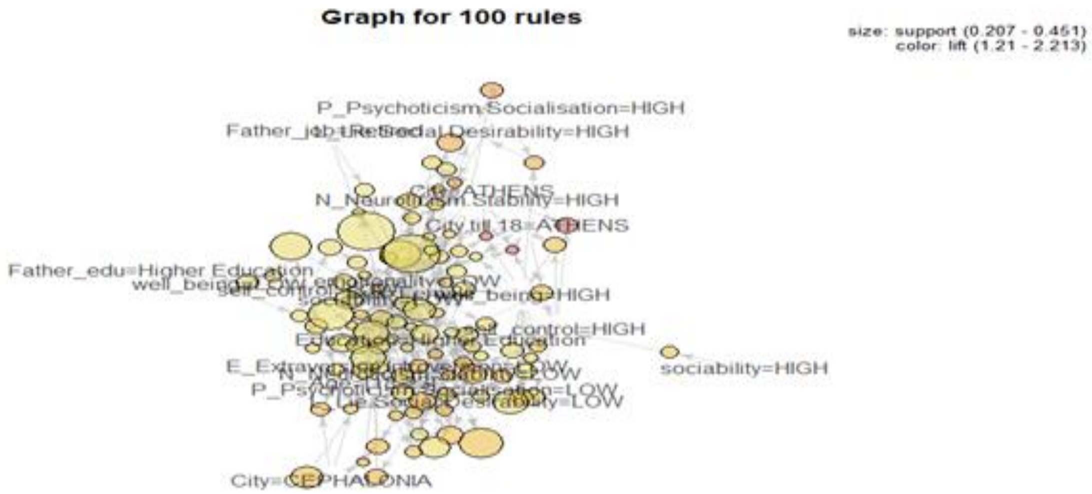

Figure 6: Graph Rules

- **Grouped Matrix plot**

Antecedents (columns) in the matrix are grouped using clustering. Groups are represented as balloons in the matrix (Figure 5).

- **Graph**

Represents the rules (or itemsets) as a graph (Figure 6). Specifically of our use, the parameters that were altered are:

➢ control=list(type="items")

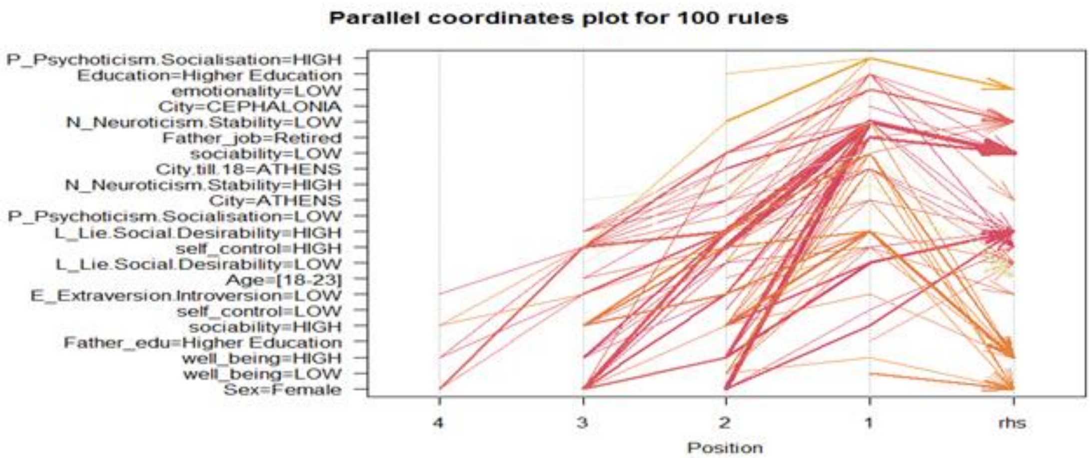

Figure 7: Paracoord Rules

- **Paracoord**

Parallel coordinate charts are a form of visualization comprised of an infinite number of vertical axes, each representing a distinct set of 61 rules, with lines drawn over the axes. Similar to scatter plots, the lines represent the relationship between the axes, and the shapes formed by the lines indicate the relationship. Additionally, we can glean information about the relationships between the axes by observing the clustering of lines (Figure 7). Consider the map below as an illustration. Specifically for our purposes, the following parameters have been modified:

➢ control=list(reorder=TRUE)

Apriori rules

After the extraction, the **top 12 rules**, also, presented lift approximately 1.

Lhs rhs support confidence lift

1. Age=[18-23], L_Lie.Social.Desirability=LOW, self_control=HIGH,sociability=LOW => {E_Extraversion.Introversion=LOW} 0.1097561 0.9000000 1.447059
2. {Age=[18-23], Mother_job=Housekeeping, well_being=HIGH, sociability=LOW} => {E_Extraversion.Introversion=LOW} 0.1097561 0.9000000 1.447059

3. Sex=Female, Mother_edu=Higher Education, self_control=HIGH} => {E_Extraversion.Introversion=LOW} 0.1097561 0.9000000 1.447059
4. {Mother_job=Public Servant, self_control=HIGH} => {E_Extraversion.Introversion=LOW} 0.1097561 0.9000000 1.447059
5. {Education=Higher Education, P_Psychoticism.Socialisation=LOW, N_Neuroticism.Stability=HIGH, sociability=LOW} => {E_Extraversion.Introversion=LOW} 0.1219512 0.9090909 1.461676
6. {City=CEPHALONIA, L_Lie.Social.Desirability=LOW, self_control=HIGH} => {E_Extraversion.Introversion=LOW} 0.1219512 1.0000000 1.607843
7. {Education=Higher Education, N_Neuroticism.Stability=HIGH, self_control=LOW, sociability=LOW} => {E_Extraversion.Introversion=LOW} 0.1219512 1.0000000 1.607843
8. {Sex=Female, Age=[18-23], City=ATHENS, sociability=LOW} => {N_Neuroticism.Stability=HIGH} 0.1219512 1.0000000 2.050000
9. {Sex=Female, Age=[18-23], self_control=HIGH, emotionality=HIGH} => {N_Neuroticism.Stability=LOW} 0.1341463 1.0000000 1.952381
10. {Age=[18-23], City=ATHENS, sociability=LOW} => {N_Neuroticism.Stability=HIGH} 0.1341463 0.9166667 1.879167
11. {City=ATHENS, Father_job=Retired,well_being=HIGH, self_control=HIGH} => {N_Neuroticism.Stability=HIGH} 0.1219512 0.9090909 1.863636
12. Age=[18-23], City=CEPHALONIA, self_control=HIGH, emotionality=HIGH} => {N_Neuroticism.Stability=LOW} 0.1219512 0.9090909 1.774892

IV. CONCLUSION

The findings of this study revealed disparities in terms of three (3) EPQ questionnaire markers and demographic variables such as gender. While the participants indicated elevated levels of neuroticism and introversion, the emotionality component was not found to be important in this study. In terms of gender, males tended to be more affected than females by their personality, which determines how they think, feel, and behave against themselves and others. One general conclusion can be drawn from the data in order to understand the consumer behaviour of young adults on social media. This paper has the potential to be a valuable marketing aid in deciphering young adulthood's developmental problems in the area of emotional maturity between males and females.

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