Contextual Gamification Platform based Big5 Personality Trait and Preference Selection for User Recommendation

By

Mahbubul Islam and UIU ID : 012201011

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Department of Computer Science and Engineering
United International University

Abstract

The emergence of social networks has led to the development of many methods to evaluate people's personalities based on their language usage and social interactions. Additionally, performance in numerous downstream tasks including sentiment analysis, text summarization, question answering, creating recommendation systems, and so forth has increased due to recent developments in deep learning-based language models. In addition to that, gamified environment attracted users more attention in any system. Gamification and the availability of social media data for personality-based preference selection have drawn the attention of researchers due to the growing need for personalized services. This research aims to examine the prediction of Big5 personality and personal preference based recommendation using text analysis, where we use a gamification based platform to understand user selection. Using a locally obtained data set, we investigate the prevalence of social network arrangement and linguistic elements concerning personality interactions. We also deploy a game based platform to assess personality based preference. We assess and compare four machine learning (ML) models and a multimodal deep learning (DL) architecture paired with Bidirectional Encoder Representations from Transformers (BERT) as a pre-trained language model as a feature extraction approach on both social media data sources and gamification platform sources. The prediction accuracy reveals that, even when evaluated with a comparable data set, the preference prediction system built using BERT-based features with Long Short-Term Memory (LSTM) and Neural Network (NN) outperforms the average baseline with a prediction accuracy of 97%. The capacity of algorithms to considerately determine a candidate's personality-based preference to employ a game like environment and simple textual content from Facebook or textual expression opens up considerable prospects to eliminate the subjective biases associated with traditional recommendation systems.

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Publication List

The main contributions of this research are in preparation in journals and conferences, as mentioned in the following list:

Journal Articles

1. Contextual Gamification: Unveiling User Preferences through Big5 Personality Traits and Text Based Analysis

Conference Papers

1. Gamification in Personality Assessment: A Comparative Analysis

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Chapter 1

Introduction

The rise of social networks has sparked the creation of numerous techniques to assess people's personalities through their interactions on social media in order to provide more insightful recommendations. Because of their monotonous and uniform platform, traditional systems fail to appropriately attract and retain the attention of the user. In any system, gamified environments obtain more attention and attract users, increasing their appeal and motivational affordances as well as provide recommendation. There is an increasing desire for individualized services, and gamification and social media data availability for personality-based preference selection offer a solution. Our goal is to create a user recommendation system that uses contextual gamification to identify users based on their preferences and personalities, thereby increasing their attraction and motivation.

1.1 Motivation

Social network platforms such as Facebook and Twitter have become some of the most prevalent destinations for internet users in last decades. The development of information has accelerated, particularly in the form of textual data. Through these social network activities provide an excellent platform for academics to examine and comprehend individuals' online habits, interests, and personalities. Previous research [1, 2, 3] has found a high association between user personality and online behavior on social media. Applications that can benefit from user personality information include, to name a few, recruiting systems, personal counseling systems, internet marketing, personal recommendation systems, and bank credit scoring systems [4]. Though, recommendation platforms are not highly correlated with personality preference, modern recommendation systems highly decorate with gamification elements. Gamification elements and dynamics can be utilized to a different extent, such as sociopsychological and cognitive domains, to extract better user's preference [5]. Gamification elements may motivate and engage users in the short term. However, they often only do so for a short time, and research by [6] has shown that external rewards weaken users' internal motivation over time [7]. The drawback of the current recommendation system is the need for more personalization of the gamification features that best fit to the individuals. A research [8] developed a system for personality acquisition through gamification that was based on the popular Big5 model using a series of interactive and contextualized questionnaire based web system was able to accurately infer a user's preferences. Another researcher [9] presented a system for recommending recipes based on Big5 personality types for each recipe in order to remove cold start issues, apply suggestions for new users based on network graphs and reviewers' feedback. A hybrid learning model was presented [7] to help online foreign language learners become more motivated and successful academically by correlating personality attributes with gamification. Numerous research conduct based on personalized gamification, though none of them are contextualized. We aim to provide a context-based gamification platform selection for personality and preference in order to address this gap.

Our study focuses on the strong correlation between social network use and personality-based preference.This study aims to design a Hybrid Model that uses text analysis and gamification based personality preferences to make suitable recommendation systems that increase user motivation and attraction.

1.2 Project Overview

A setting for improving services with interesting elements and user interaction to produce a game-like experience and improve behavioral outcomes is called gamification [10]. There are several situations where gamification can be applied, including government, healthcare, sustainability, transportation, and education. Moreover, industry and research employ personalized gamification to increase user attractiveness for recommendations. A person's personality is a lasting characteristic that characterizes the ways in which they interact with their surroundings. Research suggests that genetic factors, including inheritance, environment, and situation, significantly influence personality traits [5]. Personality is linked to physiological processes. Researchers have developed systems that engage users through the use of personality and gamification, however these systems are not widely used due to their homogenous platforms; conventional systems also struggle to effectively draw in and keep users [11, 12]. To address this gap, We are planned to develop a context-based gamification platform selection for personality predication as well as best preference selection for better recommendation.

This study focus on predicting users preference(i.e, Movie, Sports, Travel, Eating) from social network data, including developing an exact gamification platform for preference selection to provide better recommendation system.

Our study predicts user preferences on the Facebook social media network based on individuals' personalities, social behaviors, and language-use patterns. We use Ten-Item Personality Inventory(TIPI) [13] to choose the most valuable elements for each personality attribute and properly predict the user's preference. Following that, we develop and implement one linguistic feature, Linguistic Inquiry and Word Count (LIWC) [14], and two linguistic Natural language processing (NLP) features, Term Frequency–Inverse Document

Frequency (TF-IDF) [15] and Bidirectional Encoder Representations from Transformers (BERT) [16]. Next, we investigate the relationships between each feature set and personality attributes. We then test the characteristics' prediction potential by predicting each personality attribute. Finally, we implemented machine learning (ML) and deep learning (DL) algorithms on the prediction model. As baseline approaches for the prediction model and the related feature data for classification comparisons, we employ four distinct machine learning algorithms and Long short-term memory (LSTM) [17] with a distinct neural network (NN) based model.

1.3 Objectives

The following are our study's fundamental contributions:

- Designing user's contextual gamification platform, where accurate personality traits can be extracted.
- A pipeline has been established that links user personalities and preferences to their behavior on social networks and their preference selection.
- Two approaches for modeling language have been explored: open-vocabulary based(TF-IDF) and dictionary-based closed-vocabulary using LIWC.
- A deep learning architecture utilizing BERT, a pre-trained language model, and additional NLP features, such as TFIDF, has been developed for predicting user preferences across various domains like movies, sports, traveling, and food.
- A gamification-based framework has been designed and developed to predict user personality and make personalized recommendations.

1.4 Organization of the Report

The remaining section of the paper is organized as follows: Chapter 2 discusses the preliminaries of study and related studies in personality preference, text based personality and gamification centric personality. In chapter 3, we conduct the methodology accordingly to introduce and describe detailed methodology and design description. Chapter 3.1 describe the dataset's properties and after that chapter 3.2 illustrates the data representation. The following part of the article chapter 4 which denote model building including feature selection then Chapter 5 named results and findings has analyzed the classification results and shows the accuracy using different prediction models using TIPI, LIWC, TFIDF, and BERT features. Accordingly, chapter 5.1 have a brief discussion of project findings. Finally, concludes our investigation and makes recommendations for further research in chapter 6.

Chapter 2

Background and Literature Review

In this section. we have included a brief summary and compilation of the background, including relevant studies. Gamification and human personality are discussed in detail in the background section. Accordingly, we have discussed related work overview and contribution in the field of Personality based preference, text based personality acquisition application, and lastly gamification based personality.

2.1 Background Study

This section aims to provide a detailed background on Gamification and personality. The concept of Gamification will be defined, and its various classifications, including significant elements, will be discussed. In addition, we will explore the essential paradigm of the Big5 personality traits and give an overview of the Big5 personality instrument.

2.1.1 Gamification

Gamification [18] is a strategic technique that combines motivating affordances with user participation. The strategy employs game components and game design concepts (dynamics and mechanics) in a non-game circumstance [19]. It may also be defined as a set of actions and procedures that utilize the features of game components to design activities more game-like. Gamification can be used in various settings, including healthcare, sustainability, entertainment, government, transportation, and education. Robson et al. [20] designed a gamification technique around three principles: mechanics, dynamics, and emotion which are known as MDE. Despite the fact that gamification design uses MDE technique there are other gamification design. Liu et al. [21] has come up with two major categories: gamification objects and gamification mechanics. The term "object" refers to game components such avatars, visuals, audio effects, animation, virtual items, stories, badges, and leaderboards.

The core building blocks of gamification applications are game design components. Points, badges, trophies, leaderboards, performance graphs, meaningful storylines, avatars, and social platforms are all standard game design components [22].Those game elements are also developed game mechanics. Gamification mechanics describe play patterns of user. Interaction between game elements and user or player is called as dynamics. Level, points, competitions are used for grow dynamics. Emotion states, the impulsive response of a player while playing. According to a study by Tang and Zhang [23], each gamification elements provide a particular experience, such as motives, engagement, and attraction. Badges, points, scores, levels, and prizes are utilized to signify performance status, while the plot, mission, avatar, and role-playing engage players into the game's basic elements. Social aspects and teamwork also demonstrate how important and powerful individuals are in society, and graphics, animation, sound effects, and customization boost the quality of the gaming experience. [24].

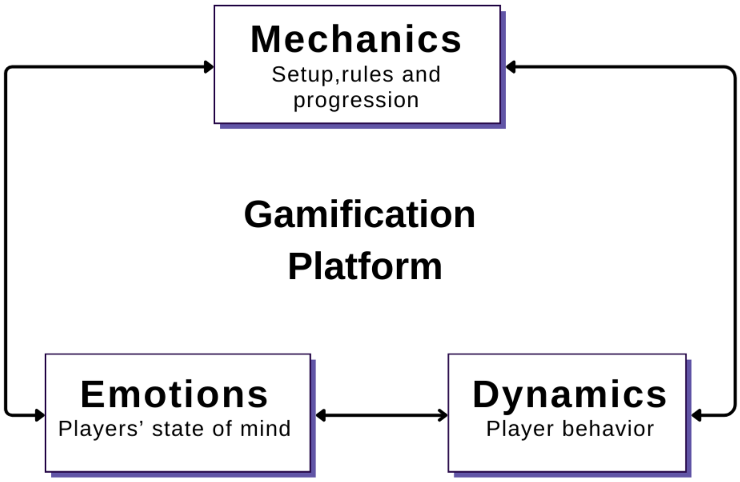

Figure 2.1: MDE based Gamification Framework

2.1.2 Personality

A permanent attribute that describes patterns of individual interaction with one's environment is called a personality. Personality is connected to physiological functions, and research indicates that genetic factors, including inheritance, environment, and situation, substantially influence personality traits [5]. In addition, previous studies have shown that personality significantly impacts people's behavior, including academic achievement and career choice [25, 26]. Three conventional personality models are used: the Myers-Briggs Type Indicator(MBTI), Eysenck's personality theory(EPT), and the Big5 personality traits, sometimes known as the Five Factor Model (FFM) [26, 27, 28]. Besides, it was observed that The Minnesota Multiphasic Personality Inventory (MMPI), which is among the most recognized standardized psychometric measures of adult personality and psychopathology, has been the focus of extensive academic research [29]. Finally, despite being less well-known than the five-component model, the HEXACO framework has received some attention [30, 31].

The five-factor model of personality (FFM) is also referred to as the Big5 model [32, 33], is a well-studied topic to describe personality. The Big5 model of personality traits is described with five major paradigms as conscientiousness (i.e., responsible, organized, and efficient), neuroticism (i.e., anxiety, inhibition, and anger), extraversion (i.e talkative, ambitious, and assertive), agreeableness (i.e friendly, cooperative, and loyal), and openness to experience (i.e curious, imaginative, and open-minded) [34]. Numerous instruments have been used to evaluate the Big Five personality traits. The NEO Five-Factor Inventory (NEO-FFI) [35] and the Big Five Inventory (BFI) [34] are the most often used instruments mentioned in the research. Each of these instruments comes in a variety of configurations. However, the majority of them belong to the IPIP pool. The full IPIP contains 3,320 items assembled by Lewis R. Goldberg [36]. Since the IPIP is public property, anyone may utilize its contents for research without restriction. Shorter versions of the IPIP pool include the IPIP100 [37], IPIP-50 [36] item pool, TIPI [13], and MINI IPIP [38].

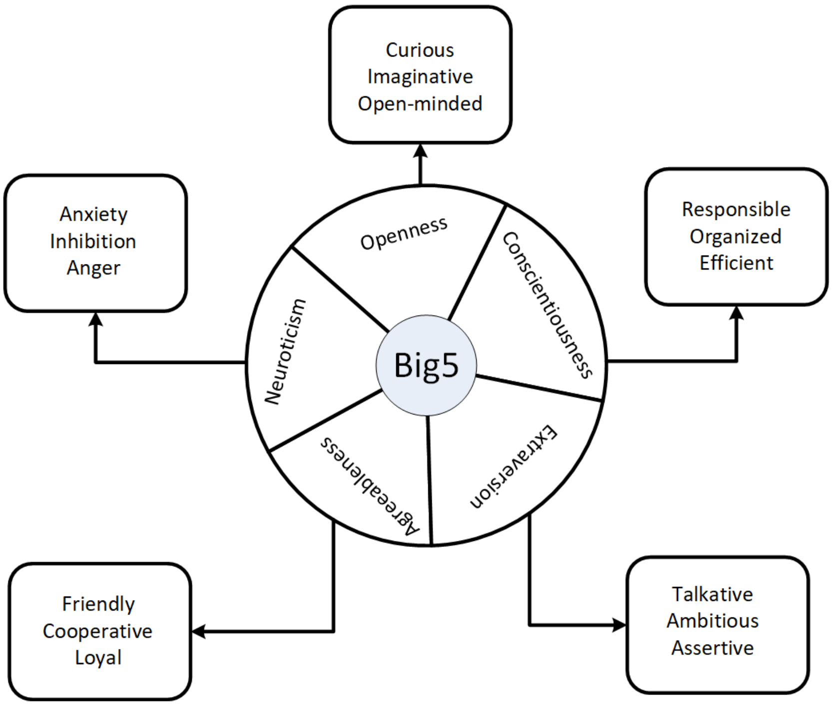

Figure 2.2: Big5 Personality traits.

2.1.3 Contextual Gamification

The mechanics, dynamics, and supported behavior of gamification are all set inside a specific context [39] for user attraction.Developing a context aware gameful environment to reduce monotony of the user for being attended a survey and get fruitful result for preference selection. In corporate context we draw specific game environment, add game content following MDE technique and game sequence for user. Game environment, content and sequence make the framework connected with user to get better outcome.

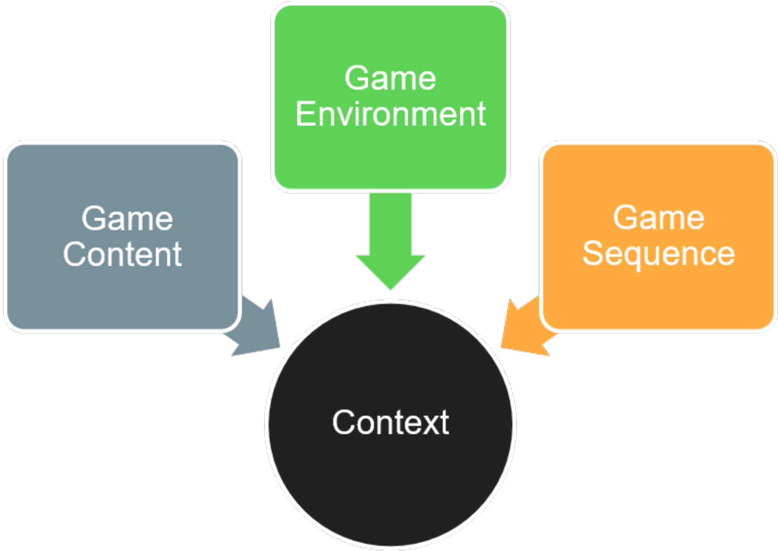

Figure 2.3: Context based game design

Gamification and personality prediction are a wide area of research. Gamification elements and dynamics can be utilized to a different extent, such as socio-psychological and cognitive domains. Personality [34] is a cognitive property that reflects patterns of individual interaction with his surroundings. Personality is linked with physiological processes, and research suggests that genetic variables significantly impact personality traits, including heredity, environment, and situation [5]. Existing techniques for personality predict by using on static questionnaires, non context text, video, audio etc. Therefore, these techniques may suffer in selecting appropriate sets of engagement and interest for personalized cases. Lack of interest or participation in an activity has been proven to result in random replies or successive similar responses, known as straight lining. Faking and careless replying are examples of error variation that affect the validity of survey results [40].We believe that the application of gamification can mitigate these problems.

2.2 Literature Review

In this section, we have discussed in detail about previous studies related to personality and preference, text based personality and gamification based personality separately. A summary of related studies has been provided in Table 2.1.

2.2.1 Personality and Preferences

Several studies have found a substantial link across user preferences and personality. Different types of content seem to appeal to different types of users. These relationships depend on the domain. This kind of data is quite helpful when creating a recommender system for a certain domain.

According to a study by Gao et al. [41] persons with identical personality features have similar purchase natures, including a strong likelihood to buy things after reading a review from people with similar personality traits. Davies et al. [42] conduct a study that displayed that people who are open to new experiences buy more corporately named products than extroverted people. Also, for the question of how personal factors affect where people choose to travel, many studies showed that personal factors do affect where people choose to travel. However, it has also been found that not all personal factors help decide on traveling tendencies. However, there is some connections between personality and traveling preference [43]. Chausson et al. [44] experimented to see if there is a link between the Big5 personality traits and the types of movies people like to watch. The author showed that personality factors play a significant role in determining what movies people like to watch. The types of movies a user likes to depend on their personality. Also, people's penchant for rating movies is strongly linked to particular personalities [45].

2.2.2 Text Based personality

In a study, Hans [1] employed a novel personality evaluation prediction method that extracts features from social media data sources by combining a multimodel deep-learning framework with a range of pre-trained language models, including BERT, RoBERTa, and XLNet. Facebook and Twitter are two social media sites used in this study to construct a prediction model for each attribute, utilizing a bidirectional context feature in conjunction with an extraction approach. Finally, the algorithm decides to make a forecast based on model averaging. According to another study [46], based on an online chat interview with over 46,000 job candidate, personality traits related to past behavior and situational judgment were deduced from the interview material. This included a personality evaluation using the six-factor HEXACO personality model for the self-rating personality. They created a regression model using machine learning and natural language processing (NLP) to infer HEXACO trait scores from textual content. Algorithms' ability to objectively determine a candidate's personality based just on the text of interview responses that suggests the possibility of eliminating the subjective biases present in human interviewers' assessment of applicant personalities [46].

Research by Tadesse et al. examined the prediction of Facebook user personality traits based on various aspects and metrics of the Big5 model. Utilizing the "My Personality" a well-known online free dataset, consider whether social network architecture and language construction are present concerning personality interactions. Also examine the relationships between each feature set and personality qualities in four machine learning models, compare them, and interpret the results [47]. Several statistical variables taken from the input text are merged with text embedding's from big language models like BERT and the self-attention mechanism in a study's proposed personality prediction system [48]. The Kaggle dataset for the MBTI was used in an experiment that conclusively demonstrated that including text statistical characteristics increases system performance compared to utilizing only BERT embedding's.

Another study construct a standard effort to infer user personality from Facebook user data based on the Big5 model personality and makes an effort to put into practice a few deep learning architectures to compare them using a thorough analytical approach and accuracy results [49]. In addition, a study by Golbeck [50] showed, Big Five personality characteristics predicted from the publicly accessible information they provide on Twitter via user profiles utilizing the Twitter API. The research predicts scores on each of the five personality qualities using machine learning algorithms, ZeroR classifier and Gaussian distribution processes, and found substantial results.

2.2.3 Gamification based Personality

Users' personalities and behavior on gaming platforms are linked, and personalities have differed from goals and motivations in a game settings [51]. According to a study [52], playing the video game "Fallout 3" can reveal information similar to taking a personality test. Additionally, studies examined how "Neverwinter Nights" a well known game can interact players with one another and discovered a link between each player's personality profile and their behavior in-game [51, 53]. Feben et al. [8] concentrated on creating a personality acquisition method through gamification that was based on the popular Big5 model. Through a series of interactive and contextualized questions, a web-based system was implemented that was able to accurately infer a user's preferences which is not possible to detemine looking at their written content in context. Adaji et al. [9] presented a system for recommending recipes based on five personality types for each recipe: neuroticism, extraversion, conscientiousness, agreeableness, and openness. In order to remove cold start issues, apply suggestions for new users based on network graphs and reviewers' feedback, and illustrate recipes such as meat or vegan.

A hybrid learning model was presented by Kang et al. [7] to help online foreign language learners become more motivated and successful academically by correlating personality attributes with gamification.Zhao et al. [54]examined participant preferences for physical activity to propose and test the design of a personality-based physical activity recommender system for exergames. Table 2.1 presents different studies related to gamification based personality prediction and recommendation systems. According to a study by Airlie Hilliard et al. [11], a forced-choice, image-based evaluation has the potential to be a reliable method of evaluating candidates' personalities throughout the hiring process. However, they spoke about the consequences of hiring practices and policies and the requirement for more validation. With the IPIP-NEO-120 technique, all models demonstrated high levels of convergent validity; however, additional research with bigger sample sizes is required more firmly evaluate this. A research by Triantoro et al. [24] suggested a gamification approach that will raise respondents' interest and attentiveness, improving their perceptions of the surveying organization. They designed a gamification framework that can collect user personality scores from the Big Five personality traits such as agreeableness, conscientiousness, extraversion, neuroticism, and openness, in order to answer

Table 2.1: Comparative analysis among different Personality acquisition approaches

Gamification	Context based approach	Machine learning based approach	Deep learning based approach	Sample size	Preference
✓ [32]	✗	✓	✗	549	✗
✓ [8]	✗	✓	✗	33	✗
✓ [9]	✗	✓	✗	178	✗
✓ [54]	✗	✓	✗	38	✗
✓ [57]	✗	✗	✗	158	✗
✓ [58]	✗	✓	✗	213	✗
✗ [1]	✓	✗	✓	752	✗
✓ [24]	✓	✓	✗	694	✗
✓ [11]	✓	✓	✗	731	✗
✓ [59]	✓	✓	✗	10	✗
✓ [12]	✓	✓	✗	343	✗
Our Research	✓	✓	✓	263	✓

these concerns. According to the findings, people love gamified surveys more and pay closer attention when completing them. Boot et al. [55] literature review looked at how video games can be utilized to research cognitive functions. In contrast, another study by Gray et al. [56] suggested that game data analysis could provide insight into human performance theories and the progression of players from novice to expert. Researchers believes using gaming data to strengthen social, behavioral, or cognitive theories will be advantageous.

2.3 Gap Analysis

By structuring the personality assessment as a game or game like environment, it should decrease fabrication and thoughtless responses by enhancing the participants' intrinsic interest and involvement. This approach can circumvent typical problems with personality assessment, and traditional questionnaire theories might perform better in terms of precision and accuracy of data [40]. Numerous research confirms that new research areas for personality assessment include incorporating game aspects and offering scenarios and alternatives via a game platform. It is observed from the literature that the method of personality prediction using gamification techniques are more focused on how it successfully engages the user, while not based on individual personality traits. Existing techniques predict based on static questionnaires, educational apps, non context game based assessment(GBA), image, video, audio etc. Therefore, these techniques may suffer in selecting appropriate sets of screenplay for personalized cases.There are high probability to reduce interest, engagement and motivation.In the literature, no study was found which can predict different personalities based preference using context-based gamification platform. We fill this gap according to the state of the gamification-based personality prediction studies.

All users are not comfortable with the same gameful environment, so a context-based platform is immensely significant in deferring the personality than proposing the recommendation. We aim to focus on that gap and implement a novel method to develop a context-based gamification platform to predict personality and preference using a word embedding system.

Chapter 3

Methodology

This chapter outlines the detailed methodology and design for the study on predicting Big5 personality and user preferences using a contextual gamification platform. The chapter begins by introducing the data acquisition process, including the extraction of textual responses from Facebook, conducting surveys to obtain Big5 scores and understanding user preferences. It then describes the development of the gamification-based platform that collects data and predicts interest domains. Finally, the chapter provides details on the gamification framework, game elements used, and the illustration of gameplay. The aim of the study is to validate whether a game-like environment can predict personality and preferences accurately.

3.1 Data Collection

This chapter includes details on the survey conducted to gather Facebook posts and written responses, the use of the TIPI-10-based survey for personality analysis, the gamification platform developed for data collection, participant demographics, data normalization, and data preprocessing. The chapter offers a thorough summary of the methods utilized to guarantee the precision and dependability of the data as well as the procedure for gathering the data.

3.1.1 Survey

Table 3.1 illustrates the summary of data collection. We cumulate Facebook posts from 263 users by mailing and word of mouth technique. Users range in age from 18 to 50 and are drawn from the professional and university communities. By September 30, 2023, we only have 12,000 Facebook English statuses. The gathered statuses' maximum, minimum, and average word counts are 2500, 100, and 500, respectively. We also ask a common open question to all users to collect the written response. We fetch 263 user data by using open questions with at least 100 words for each response and a sum of 7000 words in total.The gathered tests' maximum, minimum, and average word counts are 200, 100, and 140, respectively.

Table 3.1: Data collection summary

Attributes	**Statistics**
Number of users	263
Number of domains	4 (Movie, Sports, Traveling and Eating)
Number of sub-domains	Each domain have 5 subdomains (ex : thriller, drama for movie Mountain and hill tracks for traveling. Strategy Game, Invasion games for sports Fast food, Street food for eating)
Avg. # number of words in users open hand writing	100
Avg. # number of words in users FB post	250

Longer personality instrument may be impracticable in some study [13] because participants face difficulties due to more time-consuming. Therefore, We use the TIPI (10 items) to achieve a user-friendly personality prediction, in which way participant's degree of engagement and precision is maintained. TIPI comprises ten bi-polar elements representing one of the Five-Factor Model's high and low poles. The scale is outlined to assess personality in the factors of 10 questions about users based on big5 traits and reverse traits of each, such as extraversion versus introversion, open-mindedness versus close-mindedness, emotional stability versus neuroticism, and agreeableness versus disagreeableness, Conscientiousness versus being disorganized [60]. TIPI's response options are in the form of a 7-point Likert [61] scale which contains points like disagree strongly, disagree moderately, disagree a little, neither agree nor disagree, agree a little, agree moderately, and agree strongly. Every response has its numerical value (from 1-7) to represent the scoring somewhere on the continuum between the two bi-polar forms of each trait.

We select four domains named movie, sports, traveling, and eating habit as user's preference, and every user selects a favorite domain for himself including a rank of the subdomain of each domain.

3.1.2 Gamification based data collection

For the research purpose, We develop a gamification platform to improve used interaction while data collection.There are five separate level including contextual screenplay.We have implemented the underlying scenario based on 50-item IPIP Big-Five Factor Marker. We select 20 questions based on five facets of personality and choice the best facet to measure [36, 62]. Then, it fits the backend to the game environment. It takes most people 10–15 minutes to complete the whole game.

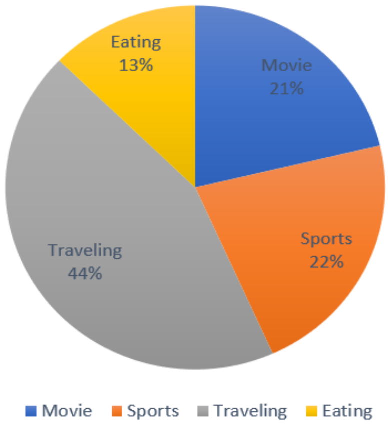

Figure 3.1: Users preference frequency

Participants

To take a response from the user, we invited some participants to respond to the gamification platform, we received a total of 263 responses denoted in Table 3.2. We filtered the data to ensure the participants completed the TIPI response using a Likert chart, provided the best preference, and answered the open question. Of these responses, 61.9% were aged between 18-22, 35.3% were aged between 23-28, while 2.3% and 0.5% were aged between 29-35 and 36-40, respectively. The majority of the participants 83.4% were male, while 16.6% were female. Regarding educational level, 61.9% held Bachelor's degrees or similar, 34.4% were studying for a Bachelor's degree or similar, 2.8% held a Master's degree or similar, and only 0.9% had completed high school. In terms of occupation, 79.2% were full-time students, 15.4% were employed for wages, 1.9% were self-employed, and 3.5% were both students and service holders.

3.1.3 Data Normalization

Normalization is a pre-processing step, a mapping technique, or a scaling approach. From an existing range, it can use to find a new range. It can be quite beneficial for forecasting or prediction purposes. To bring them closer, the normalization technique must be used to maintain the wide difference in forecasting and prediction [63].By using these methods, one may guarantee that the data is on the same scale, lessen the effect of outliers, and enhance model performance. We applied the scaling approach known as min-max normalization [64] for both survey and gamified data, which shifts and rescales numbers until they fall between 0 and 1. Here's the formula for normalization:

$$Min - Max\ Normalization = \frac{max(x) - f(x)}{max(x) - min(x)}$$

Table 3.2: Participant Demographics

Category	Total Participant = 263
Age	18-22(61.9%)
	23-28(35.3%)
	29-35(2.3%)
	36-40(0.5%)
Gender	Male(83.4%)
	Female(16.6%)
Educational Level	High school(0.9%)
	Bachelor degree or Similar(61.9%)
	Studying in Bachelor or similar(34.4%)
	Masters degree or similar(2.8%)
Occupation	Student(79.2%)
	Employed for wages(15.4%)
	Self-employed(1.9%)
	Student & Service holder(3.5%)

3.1.4 Data Preprocessing

Preprocessing involved deleting any irrelevant data from user responses, such as stop words, special characters, digits, and URLs. In addition, the answers were converted to lowercase and lemmatized to remove repeated terms. It's also typical to see Bangla terms written in English characters on social media, and these words can result in incorrect tagging.The NLTK [49] package, which offers numerous linguistic functions to help clean up Facebook status data and for open text, is used in this preprocessing. These capabilities include tokenization, stemming, and stop-word dictionaries [65].

3.2 Data Representation

3.2.1 Linguistic Inquiry and Word Count (LIWC)

A text analysis algorithm known as Linguistic Inquiry and Word Count (LIWC) counts words in groups that have psychologically relevant meanings in an open-loop fashion. LIWC demonstrates its ability to identify word, as well as attentional concentration, emotionality, social relationships, thinking styles, and individual variations, through experimental analysis [14, 66].

The user will obtain an output with more than 70 columns of data when they submit a text into LIWC. The design of LIWC was originally intended for psychologists, but it is also useful in business, mental health diagnostics, social media analysis, and many other fields. Internationally, psychologists have created LIWC dictionaries in a variety of languages, including Arabic, Chinese, Dutch, English, French, German, and so on. There are 4500 words and word stems in the LIWC2007 lexicon. Every item is organized into one or more subcategories. LIWC creates a text using 55 word categories, one of which is represented by subdictionaries. The word "cried," for instance, falls into one of the following five word categories: verb, past tense verb, overall effect, negative emotion, and sadness. Accordingly, each of these five subdictionary scale scores will increase if it is discovered in the target text [67]. Essentially, studies have shown a relationship between the Big5 personality traits and values in all LIWC categories [68].

3.2.2 Term Frequency-Inverse Document Frequency (TF-IDF)

The Bag of Words (BoW) model, which provides information on the more and less important terms in a document, is used to form Term frequency-Inverse document frequency (TFIDF) [69].

Term frequency (TF) is a measure of a word's (w) frequency in a document (d). A word's TF is determined by dividing its frequency of occurrence by the total number of words in the manuscript. Because the corpus documents' durations differ, normalization is the denominator term in the computation. Word significance is measured via the Inverse Document Frequency (IDF) concept. Word significance is not considered by the term frequency (TF) algorithm. Some words, such "of," "and," etc., are frequently used but have little to no significance. Every word in corpus D is given a weight by IDF based on how frequently it appears in the document [70].

TFIDF is the outcome of TF and IDF. It adds greater weight to the word that doesn't appear too often in the corpus (all the texts). It lends greater weight to the term that occurs more frequently in the article. [71].Below is the formula for TF-IDF:

$$TFIDF(w, d, D) = TF(w, d) * IDF(w, D)$$

3.2.3 Bidirectional Encoder Representations from Transformers (BERT)

An input sentence's context can be understood more fully by a pre-trained model. On the task-specific dataset, the model can be adjusted to obtain acceptable results following pre-training. Thus, the name "Bidirectional Encoder Representation" (BERT), which employs deep bidirectional layers of transformer encoders for language interpretation [16].

The model architecture of BERT is inspired by Transformers [72]. For language representation, it employs multilayer, bidirectional transformer encoders(attention contextual info). Based on the model architecture's depth, two new BERT model types are presented: BERTLarge and BERTBase. BERTBase was employed in this study [16].

3.2.4 Transformer

A transformer is a type of deep learning model where each input data component is given a variable weight based on the self-attention process. It is widely used in natural language processing and computer vision [73]. Transformers are used to manage sequential input data in processes like translation, text summarization, and categorization. In contrast to RNNs, transformers process all input simultaneously [72]. A Transformer is a revolutionary type of neural architecture that encodes input data as potent qualities using the attention technique. The visual transformers compute both representations and their associations after dividing the input images into numerous local patches. The granularity of the patch division is insufficient for analyzing characteristics of objects at various scales and locations since natural images are highly complex with plentiful detail and color information.

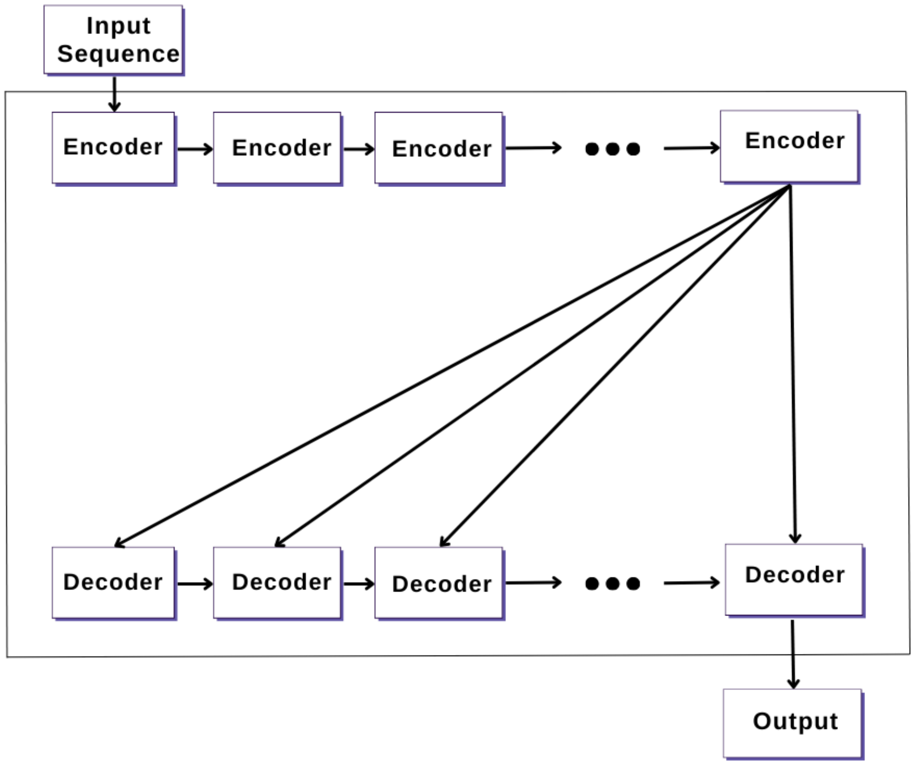

Figure 3.2: Transformer Architecture

3.2.5 Attention

Attention is a neural network-based method for imitating cognitive attention. The impact's purpose is to urge the network to pay more attention to the minute but crucial bits of input data by raising some and decreasing others. Gradient descent is used to teach an algorithm how to determine which part of the data is more important than another based on the context. The process is strengthened by using two types of weights: conventional and soft weights. Unlike conventional weights, which must remain constant throughout the runtime, "soft weights" can alter during the runtime, giving them flexibility. Attention is used in transformers for language processing, memory in neural Turing machines, reasoning in discrete neural computers, and sensory perceptions in multimodal data processing (audio, images, film, and writing) [74].

3.3 Detailed Methodology and Design

In this study, we predict Big5 personality and user preference by using contextual gamification platform and also using ground truth survey. First, we extract textual responses from user status from Facebook and text responses from open questions. We extracted Facebook data from a total of 263 users by using a random sample technique. We also conduct a survey among these users to get their Big5 scores by conducting a TIPI test. We also conduct a summary to understand users preferences. According to the survey, we collect user personality traits and preferences. Based on the survey data set, we prepare a training set and testing set to predict preference for making a baseline for the dataset.

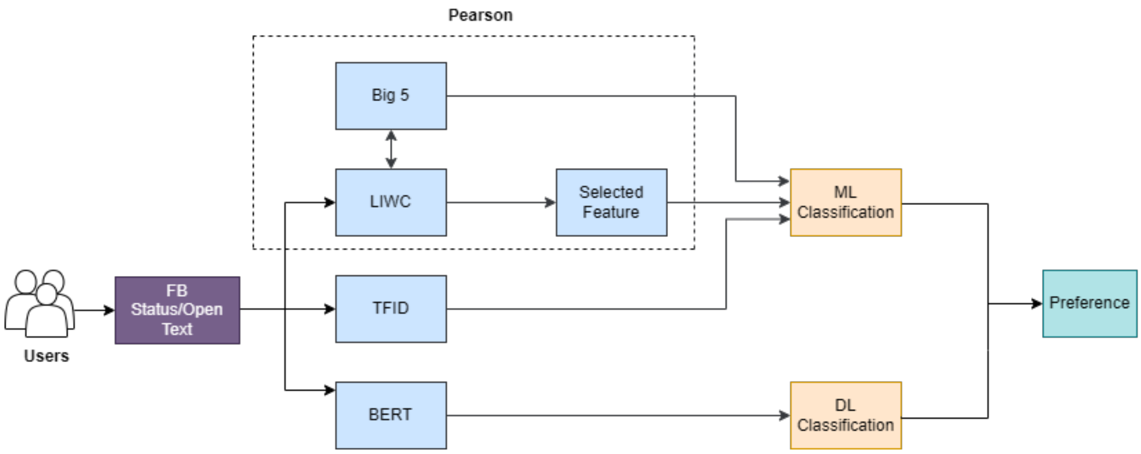

Figure 3.3: Methodology of text based Big5 Personality and preference selection

Secondly, We also develop a gamification based platform to collect data.Users face a game like situation with some contextual storyline like leadership test, challenges to overcome using emotional intelligence, intellectual quotient, and decision-making ability. We used IPIP-50 as a personality instrument to develop game screenplay.A multiple minigame and story based situation drives users to select the preference in the game.

We applied ANOVA analysis upon Big5 for feature extraction in both survey based study and gamification based study to derived best features for preference selection.After that, we apply classification models to predict the preference. After preprocessing text from both type of acquisition (Survey and game), we apply classification models to predict the preference.Before model classification, we applied LIWC. TFIDF and BERT based language model for feature extraction of text. Also applied Pearson analysis to check the transitive relation of Big5 score and LIWC significant features.Thus, we can declare it is possible to selection LIWC as model to predict preference.We found significant co-relation on Big5 Score and LIWC features.

After that, statistical analysis and word embedding technique over the posts and textual feedback of these 263 users by using, TF-IDF and BERT consecutively to extract significant features. According to the output of analysis, we run classification models to predict users' preferred domains like movies, sports, traveling, and food habits.

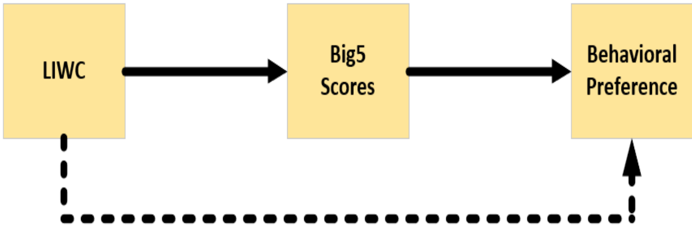

Figure 3.4: Transitive relation between LIWC features and Preference

Figure 3.4 denoted the methodology of text based Big5 Personality and preference selection.We conduct an analysis on LIWC features and Big5 score to find out transitive relation beyond them to find the correlation of LIWC features with preference.We investigate LIWC features with Big5 scores using Pearson analysis and found significant correlation among them. Thus, we validate possibility to find preference using LIWC features.Also, beside LIWC. we applied TFIDF and BERT based language model for feature extraction of text.

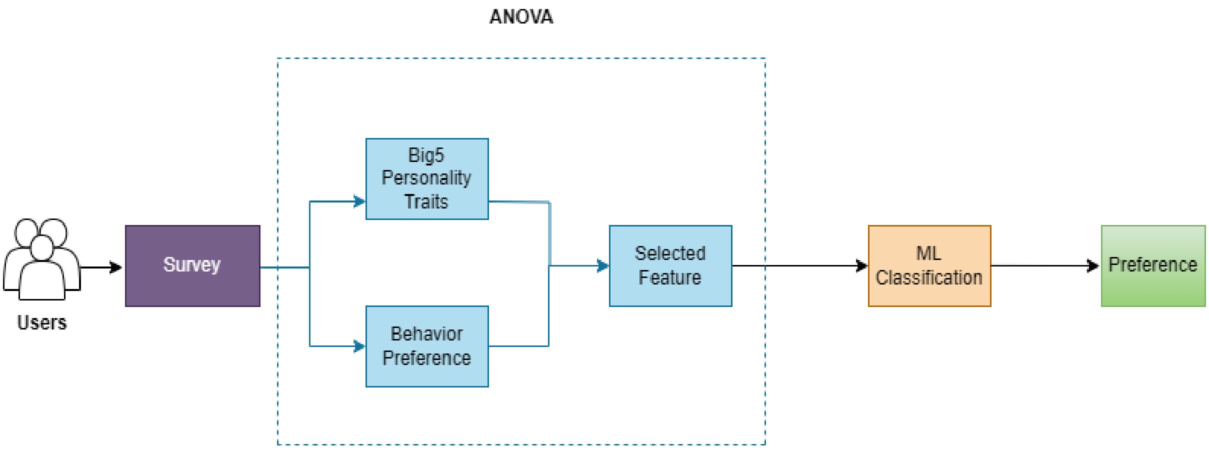

Figure 3.5: Methodology of survey based Big5 Personality and preference selection

Figure 3.5 illustrates methodology of survey based Big5 Personality and preference selection.Getting selected features employ Anova analysis, we conduct ML based classification for predict preference.

3.4 Development of Game based assessment

Gamification framework based on game elements, mechanics, dynamics and users emotion perspective discuss in the gamification framework section. Game development, illustration of gameplay and user feedback discuss in the last subsection.

3.4.1 Gamification Framework

Gamification depends on using game elements to improve test-takers responses and reactions to the assessment. There are multiple frameworks for gamification platform development, and there are concepts on how game elements may influence positive aspects like engagement and performance [12].

We employ points, levels, a leaderboard, an avatar, and a timer as game elements. Fig 3.3 illustrate the functional prototype of gamification platform in accordance with game elements. These elements can draw the mechanics of the platform.The point system functions as a success or accomplishment index. Points can be invested in order to advance the goals and utilized as incentives [75]. We have added points to the framework highlighted in the leaderboard to increase engagement [76]. Games are designed with the level system in mind to give players a sense of progression [77]. The goal of a leaderboard is to maintain user engagement by encouraging users to move their names up in honor of their achievements. The overall score of the current scorers is shown on a leaderboard [76, 78]. The virtual representation of the player, known as an avatar, has been described and examined in two studies [79, 80].

As a context-based storyline, a user can face different demanding situations throughout the game. Users can overcome or get swamped by this situation by their personality, called a challenge. Multiple options for a problem are increased competition as well as constraints. There are a few scenarios that denote interest and personal choice. Ultimately, the goal of contextual screenplay is to make users oblivious that they are picking up new skills or completing tasks by connecting user experience with context through mechanics, dynamics, and story components.Figure 3.6 illustrates methodology of Contextual Gamification platform based Big5 Personality Trait and preference selection.

3.4.2 Illustration of gameplay

Using the flatter web development tool, we develop the "Shadowed Estate" a gamification System into practice. In order to emulate game characteristics as closely as possible without making too much noise, we decided to employ a game framework. To correctly complete each level, a user must be more concerned with "winning" than accurately following the scenario and participating in the game environment. Moreover, it might jeopardize the validity of the personality test. Flatter is an open-source, cross-platform web development tool. Due to the backing of the open-source community and the abundance of documentation, it is today most well-known web development tool. In Figure 3.7, a sample game platform interface is displayed.

In order to give players a thorough understanding of their behavior, we created a variety of gaming scenarios. The platform is a role playing game (RPG) including text response, multiple choice, image selection, mini games etc. There are five levels in the tale which reflects five personality factor, plus two bonus rounds. The game opens with a narrative where the player can spend one day working as a curator in a museum. Next,

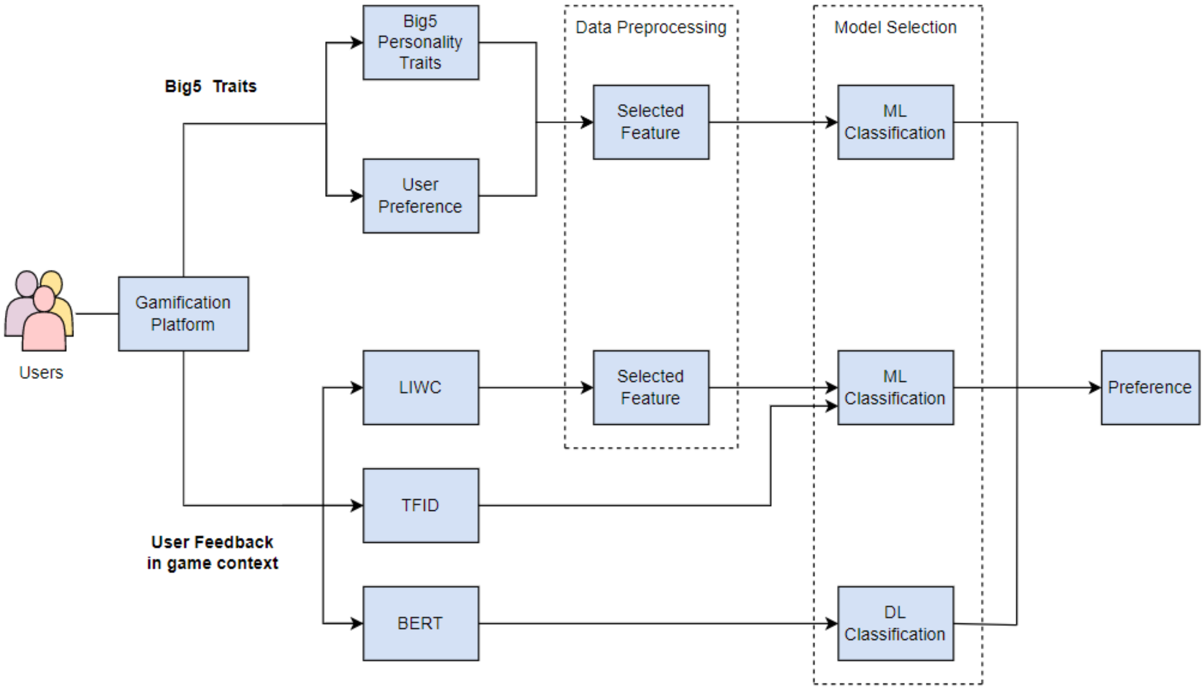

Figure 3.6: Methodology of Contextual Gamification platform based Big5 Personality Trait and preference selection

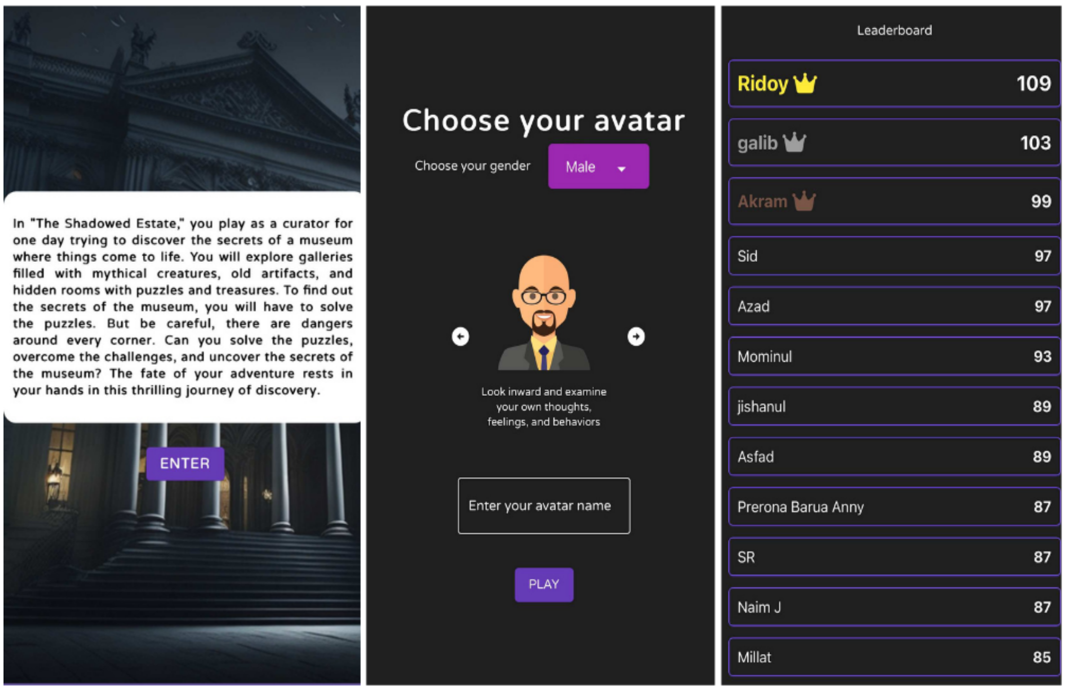

Figure 3.7: Snapshots of functional prototype of gamification platform

participants select his own personal avatar for the journey, learn how to manage organizations, resources, and leadership including faced some challenges to overcome. Finally, the narrative continues with other context-based situations, some involving decision-making and problem-solving.

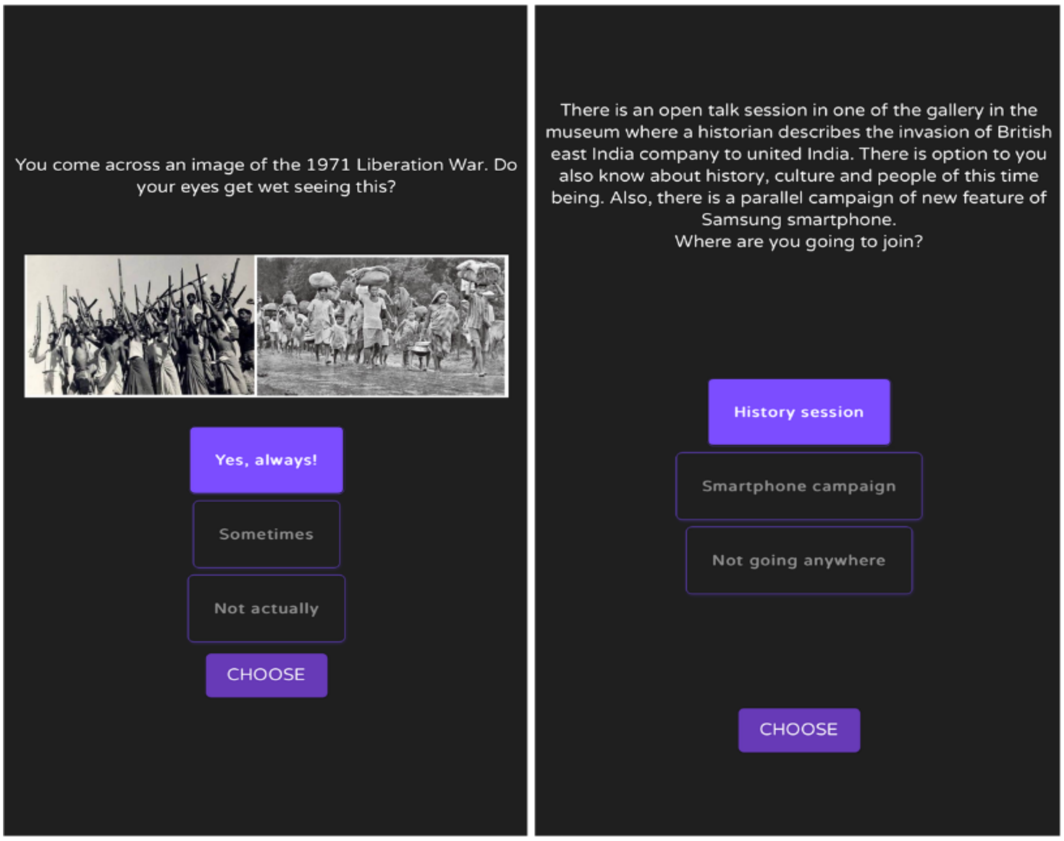

Figure 3.8: Snapshots of IPIP-50 based contextual questioner prototype of gamification platform

In "The Shadowed Estate," the users play a curator for one day, trying to discover the secrets of a museum where things come to life. Users will explore galleries filled with mythical creatures, old artifacts, and hidden rooms with puzzles, challenge and decision making. Users must solve the puzzles to discover the museum's secrets. Users can decipher the puzzles, conquer the obstacles, and learn the mysteries of the museum. This amazing quest of discovery will determine the outcome of the player's experience.

Table 3.3express the relation between selected IPIP-50 items, consecutive facets of personality scale and developed context in game screenplay.There are five consecutive level, and "L" in the Table 3.3 illustrate level of game.Every level have minimum three to maximum five contextual scenario denote by S1 to S24 in the table.

Figure 3.8 illustrates two example of game scenario of contextual gamification. As we use IPIP-50 as a personality instrument, the frontend of every contextual representation has derived from a IPIP questioner. As in Figure 3.8 left one denote traits "Conscientiousness", facets "Like order" which pole is Positive, we represent this facet as a contextual

Table 3.3: IPIP item and consecutive contextual gamification screenplay

Personality traits	**IPIP items**	**Facets**	**Contextual Screenplay**
Openness	Spend time reflecting on things.	Artistic interests	L1; S1
	Have a rich vocabulary.	Intellect	L1; S2
	Have difficulty understanding abstract ideas.	Intellect	L1; S3
	Have a vivid imagination.	Imagination	L1; S4
	Am quick to understand things.	Intellect	L1; S5
Concintiousness	Am always prepared.	Self-Discipline	L2; S6
	Pay attention to details.	Cautiousness	L2; S7
	Like order.	Orderliness	L2; S9
	Follow a schedule.	Orderliness	L2; S8
Extraversion	Am the life of the party	Friendliness	L3; S12
	Feel comfortable around people.	Friendliness	L3; S10
	Have little to say.	Friendliness	L3; S11
	Don't like to draw attention to myself.	Gregariousness	L3; S11
Agreeableness	Am interested in people.	Altruism	L4; S18
	Sympathize with others' feelings.	Sympathy	L4; S19
	Take time out for others.	Altruism	L4; S21
	Feel others' emotions.	Morality	L4; S20
Neurotisim	Get stressed out easily.	Anxiety	L5; S22
	Am relaxed most of the time	Anger	L5; S25
	Am easily disturbed.	Anger	L5; S23
	Get upset easily.	Vulnerability	L5; S24

scenario based question in level 2. Another trait "Agreeableness "and its facets " Sympathize with others' feelings" which pole is Positive, represent in contextual scenario based question at level 4 illustrates right side in the Figure 3.8.

Our research goal to finalize below assumption to test as real time environment to validate game like environment can enough capacity to predict personality and preference.

- The personality variables determined by the gamification platform exhibit a strong association with the personality factors determined by textual data and the TIPI-10-based survey.
- Compared to the survey, participants will find the GBA to be substantially more enjoyable.
- How can Gamification be used to develop a system that predicts user preferences transitively?

Chapter 4

Model Building

This chapter includes details on feature selection techniques using textual analysis, statistical analysis, and word embedding techniques. The chapter also discusses the use of classic machine learning techniques such as Naive Bayes, Support Vector Machine (SVM), Logistic Regression, Gradient Boosting, Adaboost, decision trees, Random Forest, and KNN. Additionally, a deep learning-based model using BERT and LSTM layers is developed. Finally, performance evaluation criteria such as accuracy, F1-score, precision, and recall are covered in the chapter. The chapter includes a thorough description of the model-building process as well as the approaches used to ensure the accuracy and reliability of the forecasts.

4.1 Feature Selection

To be able to keep only those with a higher potential to contribute to the prediction of preference, we implemented a filtering. We extracted features using textual analysis, statistical analysis and word embedding technique over the 1600 posts of these 263 Facebook users. We used open text response for rest of other users for feature selections. We have used ANOVA analysis and Pearson coefficient analysis to find out best features from collected dataset.We analyzed the Big5 normalized value with prefernece using ANOVA analysis.For text response we used psycholinguistic features extracting using LIWC, statistical features extracting using TF-IDF, linguistic feature extraction using BERT.

4.1.1 Analysis of variance in the Context of Big5 traits

On the Big5 personality characteristics, the Analysis of Variance (ANOVA) [9] test was conducted for calculating purposes [81]. Test significance is determined by calculating the $p - value < 0.05$ associated with a set of 5 characteristics. Three of the five studied factors were statistically significant: Conscientiousness, Extraversion, and Neuroticism (highlighted in Table 4.1 4.2).

Table 4.1: Correlation Analysis using ANOVA in the Context of Big5 traits from survey

Big5 Personality	P-Value	Accepted Hypothesis
Openness	**0.008**	HA
Conscientiousness	0.098	H0
Extraversion	**0.0051**	HA
Agreeableness	0.733	H0
Neuroticism	**0.013**	HA

Table 4.2: Correlation Analysis using ANOVA in the Context of Big5 traits from game platform

Big5 Personality	P-Value	Accepted Hypothesis
Openness	0.4735	H0
Conscientiousness	0.102	H0
Extraversion	0.5318	H0
Agreeableness	0.4014	H0
Neuroticism	**0.0003**	HA

4.1.2 Psycholinguistic Features extracting using LIWC

We used LIWC 2007 for text analysis to find the featured word. LIWC analyse sentences with the help of featured word based on 70 columns, and a dictionary contains 4500 words and word stems with various categories subcategories.

We utilized Pearson correlation, a classic feature selection approach for measuring linear correlations between two variables, to forecast the association between personality scores and extracted features [47]. There are a lot of strong links between these things, but none of them are strong enough to tell which one people will choose. After words for classification, we only use selected significant feature to avoid complexity denoted in Table 4.3.

Table 4.3: Selected feature word from LIWC for correlation analysis

Big5 traits	Correlated word
Openness	WC, WPS, number
Conscientiousness	Dic, Funct, number
Extraversion	Dic, Funct, airticle,number
Agreeableness	WC, WPS,unique
Neuroticism	WC, WPS,unique

Table 4.4: P-value analysis from Selected feature word from LIWC

Corpus	**P-value of LIWC features**							
Survey open text	**Big5 Personality**	**WC**	**WPS**	**Unique**	**Dic**	**funct**	**article**	**number**
	Conscientiousness	-	-	-	0.0585	0.0585	-	-
	Extraversion	-	-	-	0.0001	0.0001	0.0001	0.0547
Game text-1	Extraversion	-	-	-	0.0658	0.0658	-	-
	Agreeableness	0.0258	0.0258	0.0682	-	-	-	-
	Neuroticism	0.0015	0.0015	0.0096	-	-	-	-
Game text-2	Openness	0.0525	0.05259	-	-	-	-	0.03
	Conscientiousness	-	-	-	-	-	-	0.0583

Note: The first part of the table shows correlations between the LIWC selected features and Big5 traits from the corresponding survey. Consecutively, second and third part shows correlations between LIWC selected features with Big5 traits collected from game. The bolded numerical value highlights the factor correlations($p - value < 0.05$) between measures of the Big5 and LIWC features. Test significance is determined by calculating the $p - value < 0.05$.

4.1.3 Statistical features extracting using TF-IDF

To extract information from textual input, a closed loop vectorization method known as term frequency-inverse document frequency, or TF-IDF, treats words as vectors. An indication of a word's importance in a document can be found in its numerical representation. A word is considered to be more relevant to a document if it has a higher TF-IDF value than another word in a vector [15, 46]. Firstly, we extract features by using TF-IDF. A total number of 510 words extract as features demonstrated in Figure 4.1. There are 28% of verbs and 16% of adjectives, and 35% of nouns, which is the highest among them. These words are identified with weights TF-IDF for each personality measurement, indicating the relevance of that word in the personality paper.

Figure 4.1: Featured word based on TF-IDF

4.1.4 Linguistic feature extraction using BERT

We initialize pretrained model "bert-base-cased" for vectorization . The bert base model uses 12 layers transformer blocks with a hidden size of 768 and a total of 12 self-attention heads. It also has a corpus dimension size of 30,522 words and approximately 110 million trainable parameters [16, 49]. As input for the pretrained model, we transform our text into input IDs and attention mask tensors by using encode plus method.We employ BERT, an LSTM layer, and a few basic NN layers. Our classifier is found in the last set of layers after BERT. We set up our optimizer (Adam), loss function, and accuracy metric. Then, we compile the model and train denoted in Table 4.5.

4.2 Machine Learning Model

We utilized two different exploration for feature extraction: TF-IDF and LIWC in this research. We obtained 510-word extracts using TF-IDF, while LIWC produced 70 column-based numerical outputs that carried physiological meaning. Further, to build our classification model, we tested a range of machine learning models, including Support Vector Machine (SVM), Adaboost, Decision Trees, and Random Forest. Our primary objective was to juxtapose the results of ML models with a parallel DL based model. The SVM model is well-suited for classification, regression, and anomaly detection tasks, mainly in high-dimensional feature spaces [82]. It operates by locating a hyperplane in a higher-dimensional space that divides instances into distinct classes. Decision Trees, on the other hand, construct a tree-like model that examines many features and makes appropriate decisions [83]. Each node in the tree tests a feature until it eventually reaches a leaf node with a decision. Decision trees are simple to comprehend and can handle both category and numerical data, making them suited for a wide range of applications, whereas RF combines numerous decision trees that create random subsets of attributes to evaluate [84]. Combined decision-making is used to determine the final decision of the model, making it more accurate and robust than an individual decision tree. It is particularly useful when working with large datasets that have many features. AdaBoost, on the other hand, is an ensemble method that combines numerous weak classifiers to produce a more resilient and accurate classifier. It works by assigning a weight to each training instance, with misclassified instances receiving a higher weight to increase their importance in the next round of training [85]. The combined decisions of all the weak classifiers are used to make the final conclusion. In comparison, deep learning models can use deep neural networks to learn from vast amounts of data and can be effective for classification tasks that involve complex relationships between features. We aim to determine which model generated the most accurate results for classification tasks, given these feature extraction methods.

Table 4.5: Summary of hyperparameter of Bert model for using Text analysis

Network	**Bert**
Architecture	Bert Embedding
	BatchNormalization, 1
	Dropout, 1
	Dense, 3
Total Param.	Total: 108416069
	Trainable: 104261
	Non Trainable: 108311808
Epoch	50
Optimizer	Adam(0.01)

4.3 Deep Learning based Model

In the deep learning based framework, two popular models for natural language processing and prediction tasks are transformer-based neural networks and bidirectional Long Short-Term Memory (BiLSTM) models. Transformer-based neural networks have gained popularity nowadays due to their self-attention mechanisms, which enable them to capture long-range dependencies in input sequences and achieve better language modeling performance compared to LSTM-based models [86, 87]. Recent advancements in transformer models include model compression, hyper-efficient attention mechanisms, and hybrid architectures. BiLSTM models, on the other hand, can process input sequences in both forward and backward directions, enabling them to gain knowledge from both the past and the potential future settings , making them suitable for tasks with complex dependencies between input elements [88, 89]. BiLSTM has also been combined with other models such as convolutional neural networks and attention mechanisms to execute better performance. Both transformer-based neural networks and BiLSTM models are widely used in various applications in NLP and time series forecasting.

In this study, we apply BERT, an LSTM layer, and a few essential NN layers after the initial model provides the featured vector. Our classifier is located in the final set of layers following BERT. Next, we established Adam, our optimizer, the loss function, and the accuracy metric. The model is then assembled and trained.

Classification models will be differentiated and compared to a pre-trained, transfer-learning NLP-based model. After that, we divided the highlighted dataset into training and test two separate parts for each scenario. In turn, 10 % of the dataset is kept for testing, and 90% is used for training. Finally, we ran a series of tests with different scenarios to evaluate how accurately each algorithm predicted user preferences.

4.4 Performance evaluation

For classification tasks, the typical assessment criteria are accuracy, F1-score, precision, and recall, and we demonstrate all results in terms of those metrics [1, 48]. Algorithms' ability to anticipate user preferences is assessed using common evaluation criteria for classification tasks. These consist of recall, precision, accuracy, and F1-score.

The percentage of accurate predictions to all predictions is known as accuracy. This is how it is computed:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

where true positives, true negatives, false positives, and false negatives are denoted by the letters TP, TN, FP, and FN, respectively.

The average of the harmonics of recall and precision is known as the F1-score. It calculates as follows and offers a balance between recall and precision:

$$F_1 - score = 2 * \frac{(Precision * Recall)}{(Precision + Recall)}$$

The percentage of true positive forecasts to all positive predictions is known as precision. This is how it is computed:

$$Precision = \frac{TP}{TP + FP}$$

The percentage of true positive forecasts to all actual positive cases is known as recall. This is how it is computed:

$$Recall = \frac{TP}{TP + FN}$$

True positives, false positives, and false negatives are denoted as TP, FP, and FN, respectively.

Chapter 5

Experimental Analysis

In this section, we present the results of four experimental scenarios each survey and gamification platform aimed at predicting user preferences. We started by using Big5 personality traits as a basis for prediction and applied various machine learning models. In the second scenario, we employed LIWC for feature extraction, while the third scenario utilized TFIDF features for traditional ML classification. The final scenario introduced a BERT-based deep learning model. The outcomes, including accuracy and F1 scores, are detailed in Tables 5.1, 5.2, and 5.3.

We analyze the prediction of user preferences based on Big5 personality traits in the Survey and Game datasets in Table 5.1. Several machine learning models are employed, including Random Forest, Decision Tree, SVM, and Adaboost. The results provide valuable insights into the performance of these models. Random Forest and Decision Tree both yield similar accuracy scores of 35% for the Survey and 19% and 26% consecutively for the Game. The Support Vector Machine (SVM) model stands out with an accuracy of 49% for the Survey and 36% for the Game, demonstrating the highest accuracy among the four models. However, the F1-scores, while better than Random Forest, leave room for improvement. Adaboost provides results similar to Random Forest with an accuracy

Table 5.1: Preference Prediction from survey data and game from Big5 traits

Corpus	Features	Model	Accuracy	F1-Score
Survey	**Big-5 traits**	Random Forest	0.35	0.19
		Decision Tree	0.35	0.26
		SVM	0.49	0.36
		Adaboost	0.35	0.24
Game	**Big-5 traits**	Random Forest	0.19	0.19
		Decision Tree	0.26	0.26
		SVM	0.36	0.36
		Adaboost	0.24	0.24

Table 5.2: Preference Prediction from facebook and textual data collected from survey

Corpus	Features	Model	Accuracy	F1-Score
Survey	LIWC	Random Forest	0.27	0.27
		Decision Tree	0.3	0.3
		SVM	0.51	0.51
		Adaboost	0.27	0.27
	TF-IDF	Random Forest	0.384	0.384
		Decision Tree	0.31	0.31
		SVM	0.37	0.37
		Adaboost	0.29	0.29
	BERT	LSTM+NN	0.96	0.96

of 35% for the Survey and 24% for the Game, but its F1-scores are consistently lower. In Table 5.2, we explore the prediction of user preferences using features extracted from Facebook and textual data collected from surveys.

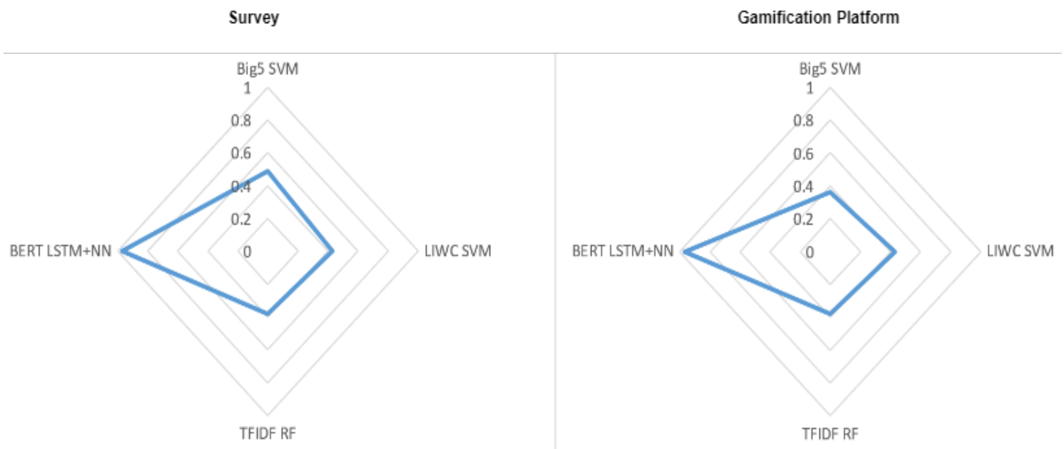

Figure 5.1: Result analysis based on accuracy for Survey and Gamification platform

When using LIWC as a feature extraction technique, the accuracy remains relatively lower, with the highest accuracy reaching 52%. However, the utilization of TF-IDF for feature extraction leads to improved accuracy, with the Random Forest model achieving a maximum accuracy of 38.4%. The F1-scores for TF-IDF models range from 29% to 38.4%, indicating superior overall performance compared to LIWC. The BERT-based deep learning model stands out with an impressive accuracy of 96%, showcasing its ability to capture complex patterns in user data, The Support Vector Machine (SVM) model consistently provides the highest accuracy, reaching 51% among the ML models.

In Table 5.3, we conducted an analysis of predicting user preferences based on textual data collected from Game, that includes data from different time points, Game text-1 and Game text-2. Here we have used feature extraction techniques like LIWC, TF-IDF, and the

Table 5.3: Preference Prediction from facebook and textual data collected from Game

Corpus	Features	Model	Accuracy	F1-Score
Game Text -1	**LIWC**	Random Forest	0.33	0.33
		Decision Tree	0.3	0.3
		SVM	0.43	0.43
		Adaboost	0.35	0.35
	TF-IDF	Random Forest	0.38	0.38
		Decision Tree	0.32	0.32
		SVM	0.34	0.34
		Adaboost	0.26	0.26
	BERT	LSTM+NN	**0.97**	**0.97**
Game Text -2	**LIWC**	Random Forest	0.18	0.18
		Decision Tree	0.26	0.26
		SVM	0.27	0.27
		Adaboost	0.26	0.26
	TF-IDF	Random Forest	0.36	0.36
		Decision Tree	0.26	0.26
		SVM	0.36	0.36
		Adaboost	0.26	0.26
	BERT	LSTM+NN	**0.97**	**0.97**

BERT LSTM+NN model. For Game text-1 and Game text-2, LIWC presented accuracy scores ranging from 26% to 35%, while the SVM model achieved the best performance with an accuracy of 43 % for Game text-1.

On the other hand, TF-IDF yielded more favorable results with an accuracy of 38 % for Game text-1 and 36% for Game text-2, and Random Forest as the top-performing model. Additionally, the BERT LSTM+NN model significantly outperformed the other approaches, achieving an accuracy of 97 % and F1-scores of 97% across both Game text-1 and Game text-2, confirming its robustness in predicting user preferences at different points in time.

These numbers, highlight the importance of choosing appropriate feature extraction techniques and machine learning models for predicting user preferences based on personality traits and textual data. While the SVM model consistently performs well, the BERT-based deep learning model stands out as the top-performing approach in predicting user preferences based on textual data, demonstrating the ability to capture complex patterns in user data. The findings provide useful insights that could be used to construct more precise and successful recommendation systems in a variety of disciplines.

5.1 Experimental Analysis

We demonstrate two-level approach to predict user personality and personality based preference according to the study. In first level, we collect ground truth data for predicting

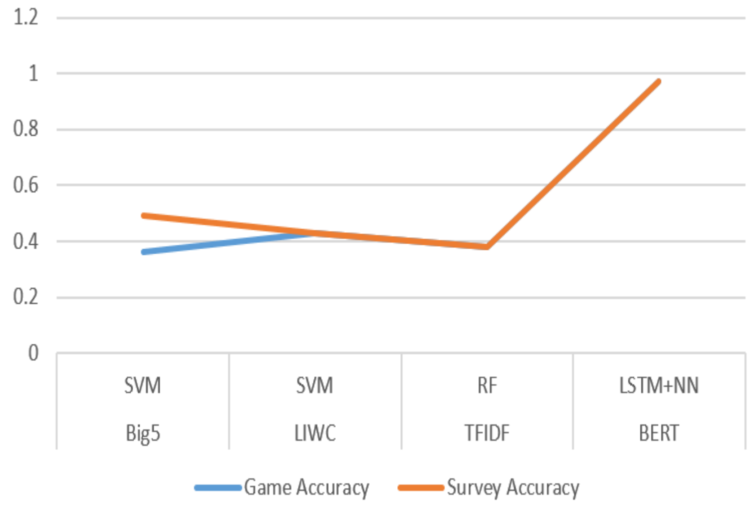

Figure 5.2: Result analysis in terms of F1-Score for Survey and Gamification platform

Big5 personality and personality based preference and alongside we utilize social media posts and text responses from open questions to calculate psychological attributes and preference of users. In second level we predict Big5 personality and user preference by using contextual gamification platform. We extracted Facebook status from a total of 263 users by using a random sample technique. We also conduct a survey among these users to get their Big5 scores by conducting a TIPI test. We also conduct a summary to understand users behavioral preferences. According to the survey, we collect user personality traits and preferences.

We also develop a gamification based platform to collect data. Users face a game like situation with some contextual storyline like leadership test, challenges to overcome using emotional intelligence, intellectual quotient, and decision-making ability. We used IPIP-50 as a personality instrument to develop game screenplay. A multiple minigame and story based situation with game elements like narrative, points, level, timeline and leaderboard drives users to select the preference in the game.

For both platform to identify the relationship with Big5 with preference by using ANOVA analysis, after that we predict the preference using machine learning model.After preprocessing from both type textual response acquisition, we apply classification models to predict the preference. We run textual analysis, statistical analysis and word embedding technique over the posts and textual feedback of these 263 users by using the LIWC, TF-IDF and BERT consecutively to extract significant features. According to the output of analysis, we run classification models to predict users' preferred domains like movies, sports, traveling, and food habits.We use the Facebook posts that individuals make on Facebook and open text reply to look into their preferences based on personality. By evaluating words using TF-IDF and LIWC in accordance with the context, we are able to

Table 5.4: Summary of best performed baseline and models

Corpus	**Baseline**	**Models**	**Accuracy(%)**	**F1 Score(%)**
Survey	Big5	SVM	49	49
	LIWC	SVM	43	43
	TFIDF	RF	38	38
	BERT	LSTM+NN	97	97
Game	Big5	SVM	36	36
	LIWC	SVM	43	43
	TFIDF	RF	38	38
	BERT	LSTM+NN	97	97

determine the semantic links between the words.The Sentence Transformer (BERT) based word-embedding vector, we carry out the context-based word embedding using an LSTM model that is based on deep learning. While essential features are typically identified by researchers using standard methods, the sentence transformer model (BERT) typically treats the entire material as a single vector. BERT has a vector size of 768. We employ non-linear approaches to predict behavioral preferences and personality in our research since the relationships between various factors are non-linear. According to our findings, the LSTM model outperforms the ML-based model. This is a result of the inability of open vocabulary systems (TFIDF), and closed vocabulary systems (LIWC) to record word relationships in reverse. On the other hand, BERT-based LSTM can find word associations in both directions, leading to a more accurate model.

The outcome of this study suggest that the use of BERT-based pre-trained models can significantly outperform traditional machine learning methods and other feature extraction techniques for predicting user preferences. The findings also indicate that closed-vocabulary and statistical techniques, such as LIWC and TF-IDF, may not be effective in predicting preferences due to the unpredictable traits of social media content. The comparison of the results obtained utilizing various situations and models emphasizes the significance of selecting the proper feature extraction and classification strategies for the dataset and task at hand. The accuracy and F1-score values differ greatly between models and scenarios, underscoring the importance of exercising caution while picking the best method.

The study also aimed to test the assumption that a game-like environment can accurately predict personality and preferences. Through the use of gamification and machine learning techniques, the study found significant correlations between the personality factors measured by the Gamified Behavioral Assessment (GBA), surveys, and textual data. The high enjoyment ratings by participants also indicate that a game-like environment can engage users more effectively in providing data for predicting preferences. These findings validate the assumption that game-like environments can effectively predict personality and preferences in real-time. Ultimately, this has important implications for developing personalized recommendations and improving user satisfaction in various domains.

In the second level, we have built a context-based gamification platform to predict personality and preference. Feben et al. [8] developed a gamified system using images, including different contexts. They suggest a gamified approach to personality assessment that includes travel-related questions for context inclusion, increasing user interest and accuracy. We also develop a screenplay based on situations that challenge the user. Also, we have employed game elements like points, levels, and leaderboards that can contextualize the whole situation and increase attraction, including motivation, based on previous literature [12, 24, 90, 91]. Triantoro et al. [24] employ a platform for problem-solving games to distinguish between a gamified survey and a conventional survey. Adding gaming features to a conventional questionnaire can make it more fun for respondents and lessen survey-related biases, as per the study. Elena et al. [91]proposed that game-based assessments (GBAs) would be particularly beneficial for capturing personality traits. Furthermore, improving usually poor candidate replies to cognitive ability and personality evaluations, or even eliminating the possibility of faking, is a common issue when measuring a personality aspect. Following previous work, we tested and developed a game-based framework to avoid conventional survey problems like casual responses, non-response bias, and common delay problems and found significantly increased the attraction of the user as they gave positive feedback about the game framework and 85% of their response is positive reflects they like the game most.

Haizela et al. [59] proposed a personality test based on a simple role-playing game. They designed a game that can predict personality based on the player's gameplay and decision-making. We obtained similar findings. In the first part of the game platform, we also predicted personality traits and preference selection. Finally, we predict the preference through personality. Christian et al. [1] introduced a new prediction using multimodel deep learning architecture combined with multiple pre-trained language models such as BERT, RoBERTa, and XLNet as feature extraction methods on social media data sources and found significant results. We also analyze the Facebook status of users by using statistical and word embedding-based large language model BERT for feature extraction. We also used TF-IDF and LIWC feature extraction. The result showed that Bert's large language model outperformed more than other methods. Mehnaz et al. [45] suggested unique strategies for predicting a user's movie genre preference and rating behavior based on psycholinguistic characteristics from social media interactions. In the survey and gamification framework, we predict personality first based on client feedback through surveys and games. We also found a significant relationship between personality and preference.

To ensure the fairness of the survey questionnaire, we asked the same questions to all participants in our study, and we developed a gamification platform based on past work [12, 24, 90] and verified from domain experts. In addition to variable selection during model construction, we carefully pick statistically significant variables that produce the highest accuracy.

It is also worth noting that the BERT-based deep learning architecture surpassed all other models, reaching a 97% accuracy and a 97% F1-score. This shows that using pre-trained models for feature extraction and deep learning approaches for predicting user preferences can be quite beneficial. Overall, this study provides useful insights into the application of various strategies for predicting user preferences, as well as highlighting the promise of deep learning-based approaches for obtaining high accuracy and dependability.

There are three main contributions of our work. Firstly, our study is the first to build and validate a framework based on gamification, anticipate user preferences based on personality, and provide tailored recommendations. The majority of earlier research predicts user personality from gamification platform using self-reported survey data [24] and few of them used gamification [8, 59] as data acquisition method. On the other hand, we use open text collected from game and real Facebook status to construct our model. In fact, a number of earlier studies [47, 48, 49, 92] have made use of real-world social media interactions, particularly when predicting personality. Therefore, our approach of using actual text to predict personality and preference from game and text collected from gamification platform. Secondly, as far as we are aware, our work is the first to construct a two-level prediction model, each with two distinct assessments based on text-based analysis and Big5 value. There is a pipeline that connects users' preferences and personalities to their choice of preferences and conduct on social networks. Ultimately, our findings support the notion that gamification-based platforms are effective in predicting user preferences and Big Five personalities.

With bert-based deep learning, our model exhibits high prediction capacity from text, with an accurate prediction in 97% of the test instances in both survey and game platform. Our technique can be used to create applications that can recognize user recommendations based on personality and preference.

Chapter 6

Conclusion

We present an overview of the main conclusions and constraints of our research in this chapter. We explore the possible ramifications of our findings and propose a number of avenues for future investigation. We highlight the significance of our contextual personality prediction system, and the effectiveness of the BERT-based text representation in predicting user preferences. Despite the limitations, our study offers an insightful offering to the field of social media analysis and personality prediction.

6.1 Summary

This study has demonstrated a novel approach to designing and validating contextual personality prediction using a gamification platform, which provides an interactive experience. In this article, we offer a contextual personality prediction framework that integrates several statistical variables from input text with text-based embedding's from large language models like BERT. Through an analysis of the relationship between users' personalities and their behavior on social networks, the study examines the available literature on social media usage as an outline for cognitive feature studies. Our findings suggest that examining the social and linguistic markers of personality and personality-based choice might provide a wealth of knowledge. We concluded that language features make intuitive sense compared to social network variables because of their enormous numbers and diversity of correlation variations. Different personalities correspond to various characteristics, as determined by computing the Pearson correlation and ANOVA analysis results between the dataset and each personality dimension. In order to infer a person's preference from their writing, we improve open-vocabulary techniques in natural language processing combined with machine learning and deep learning. We created classification models for respective traits using open vocabulary text representation techniques such as TF-IDF, one closed-vocabulary approach (LIWC), and the pertained model as BERT. Over other representation techniques, BERT-based text representation produced the highest accuracy. According to our findings, social network traits can predict personalities more accurately than the conventional open-and-closed vocabulary strategy. These findings show a more substantial possibility for contextual personality preference among individual social network traits. We could comprehend online user activity better and provide customized services by inferring personality factors based on user preferences on the Facebook social media network.

6.2 Limitation

We did not have enough participants in the survey and game to draw a thorough conclusion. Furthermore, the study's participants all had almost identical demographics. To determine the findings of this study, more individuals and a broader range of demographics are required. There were some discrepancies in the questionnaires' self-reports, and we were unable to perform significance testing for all of our variables. For instance, 70% of participants thought the experiment's duration, as presented in both the survey and game versions, was highly or somewhat fair. Only 30%, of the respondents to the comparison questionnaire stated that they didn't think any of them were very long.

We found fewer features and variety in textual data that can result in misleading the findings.Also, as the length of some Open Text is too long to answered for some user, that can also a chance to repeated word count and features.

Lastly, gamification design is a tactic that may be applied at multiple abstraction levels. This study focused on the level of gamification items and explored how game design features relate to basic human needs as seen through the lens of motivational affordances.

6.3 Future Work

More features from the network structure of the people whose Facebook posts were examined might be included as a future project to increase the feature set. As a result, to enhance our prediction system, we want to develop more datasets using other architectures in future research. Additionally, multi-modal data may be studied as signals to strengthen text-based preferences for individual personalities, such as audio and video signals recorded from user conversations.

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