Game-Based Extraction of Web Users' Personality Factors for Personalization

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ABSTRACT
The volume of information users are exposed to on the web is overwhelming. To increase effectiveness of information delivery to users, providers employ personalization strategies. In a highly competitive environment, simplistic strategies do not suffice, and high-quality personalization is required. These can be based on users' decision making models. To build such models, we need to extract factors of direct influence on users' decision making. Personality factors are known to have this direct influence. They are stable over time and across situations, and they assist in predicting future behavior of individuals in a scientific way. In this paper, we introduce a novel methodology for extracting users' personality factors without holding any prior information on the users' behavior and, notably, without administering any psychological questionnaires. This allows us to build a designated model for each user or users' group, and in turn facilitates effective personalized information delivery.

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INTRODUCTION
The volume of information delivered to users via the web has grown extensively, with some negative effects on decision making. Filtering out irrelevant information is challenging. In some cases, user models assist in such filtering. Indeed, a primary solution to the problem of information overload which assists with decision making is *personalization*. This entails adaptation of the computer system, either manually by the user or automatically, to user needs and interests. To facilitate user modeling, information such as user interests, preferences, knowledge, etc. may be required. With such information one can construct a *user model* which "is the knowledge and inference mechanism that differentiates the interaction across individuals" [1], and ultimately enables to predict user's future behavior.

In support of user modeling, this study utilizes personality psychology which introduces a formal personality assessment methodology. However, although it seems that personality psychology may assist in capturing the unique essence of a person [45], its approach to user modeling lacks automated determination of personality factors much needed for effective user modeling.

This work aims to overcome this void. We facilitate improved user modeling by automatically extracting psychological personality factors obtained from observing the user and not from direct user's input. To extract personality factors, we conduct an interdisciplinary study that identifies rational and irrational behavior patterns of human players in two-person, zero-sum games. We analyze the relationships between behavioral patterns, personality characteristics and the impulsiveness level of the players. We also examine the influence of time pressure, rewards and gender on players' behavioral patterns, personality characteristics and the impulsiveness level. The analyses we perform and the behavioral patterns it extracts enable us to build a reliable, accurate user profile and consequently provide high quality personalization.

This paper is organized as follows. We present the different approaches of extracting personality traits that exist in the art and theoretical background of our novel method. The new method relates to rational procedures in decision making and a number of influential factors on human behavior in real-life situations, including personality and impulsiveness (sub-) traits, motivation, gender and time pressure. Next, we introduce the methodology used to test our approach. Our experiment consists of a simulation of a two-person, zero-sum game followed by validation of game results through personality traits inventory and an impulsiveness scales. Afterwards, we present the experiment results. The statistical summary of our examination includes the definition of the

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experiment's variables, the statistical methodology used for each test and the final results. Finally, we present a discussion of our findings, the conclusions of our research and directions for future research.

THEORETICAL FOUNDATIONS

There are three main approaches to extract personality traits of a user or group of users (see Figure 1). The first approach for extracting personality traits is generally done through personality assessment methods such as questionnaires. Here, users are asked explicitly to rate themselves on relevant attributes of interest. This method is most widely-used. However, it may be biased when dealing with self-assessment [11] and it is usually lengthy [9] and time-consuming.

The second approach is tracking user's online behavior. This method allows us to collect information regarding users' online interaction with the websites (e.g. search, purchase and browsing behavior). It uses a variety of machine learning techniques to build detailed profiles of the users based on the collected information. However, when using machine learning techniques, it is at times impossible to get perfect accuracy, because the learning algorithm may over-fit the data thus negatively affecting prediction accuracy [21].

The third approach is online gaming. Here, users play an online game. Their personality profile is built based on analytical prediction of collected behavioral traces. It is assumed that their game activities may reveal their psychological personality and may result with pertinent personalized interface. At times, current and former approaches are employed in combination with a complementary tool – personality questionnaires – to identify (or validate) users' personality type (e.g., [9], [32], [50]).

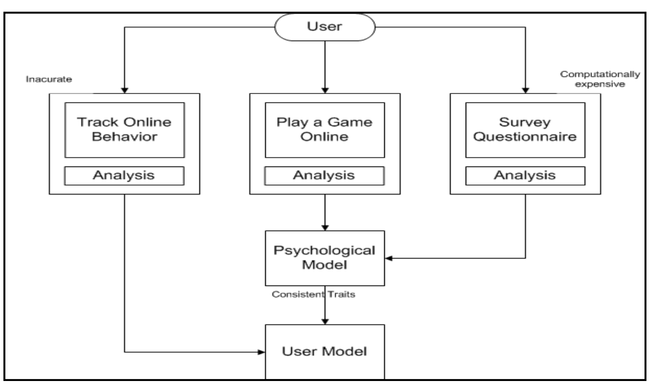

Figure 1. Three main approaches of personality traits extraction for user modeling

The following is a brief summary of previous studies that demonstrate extraction of users' personality traits in various areas. For instance, Facebook profiles and activities provide valuable indicators of user's personality. They reveal the actual personality [3]. [34] investigated personality modeling based on Facebook data and concluded that the precision of classifiers is improved when selecting the most indicative features. [47] found that the predictor for number of friends in the real world (Extraversion) is also a predictor for number of Facebook contacts. In a similar vein, micro-blogging is an ideal web-based platform to examine human psychological profiles and differences as users are motivated to make greater self-disclosure and self-presentation. [32] built models for predicting personality traits based on active users' micro-blogging behaviors.

Automatically extracting users' personality traits can also be applied to socially aware services on smartphones. [9] investigated the relationship between automatically extracting behavioral characteristics from smartphone data and self-reported personality traits. The analysis of smartphone usage features conforms to psychology literature. [18] presented a method by which a user's personality can be accurately predicted through the publicly available information on their Twitter profile. Additionally, [51] proposed a novel method that integrates user data (e.g., texts and images) from Twitter and Instagram to infer user characteristics.

Personality traits are also found to be viable and effective attributes for improving recommendations ([14], [57]). [22] demonstrated that personality quizzes are a promising way to build user profiles for recommender entertainment products. In addition, they found that novice users, who are less knowledgeable about music, generally appreciated more personality based recommenders [23].

In the games context, [50] proposed an algorithm (based on classifiers) to infer user's personality profile by using an online game. They assessed personality based on a set of cues (drawn from multiple data sources) which were generated by the player's activities in the virtual world.

The work most closely related to our own is [12]. They employed games in conjunction with psychological theories to study player modeling. They presented a new method that simplifies the comprehension of players' behavioral patterns in computer games, relying on the Temperament theory. Temperament theory assists to define what motivates a player to make game play choices. [12] study focuses on understanding players behaviors within games.

In our study, we similarly utilize games in combination with psychological theories. However, we do not focus on games and our target is not the study of human behaviors within games. Rather, we aim at the general user modeling problem, and games are used only as a mechanism for extracting significant characteristics. Thus our approach addresses the broader needs to user modeling.

Furthermore, we particularly concentrate on rational and irrational decision behaviors in games and the characteristics that influence such behaviors. Studies show [43] that users may be attuned to the goals of functional websites and consider whether the website provides an effective way of task accomplishment (i.e., rational behavior) or alternately they may attuned to goals of emotional websites and likely to continue to use websites by habit with no act of analysis (i.e., irrational behavior). By identifying and extracting the relative personality characteristics that influence rational and irrational decision behaviors, the user interface can be adapted to the user or users of the same group accordingly.

Rational decision making entails utility maximization. However, when human subjects make decisions, additional factors come to play, which are not considered in rational analysis. The major factors of interest are discussed below.

Game Theory

Game theory studies cases in which decision makers (players) use decision rules (strategies) that describe their plan of action for playing the game, as a function of their observation during the course of the game. An underlying assumption in game theory is that decision makers act rationally, choosing strategies that, according to their beliefs, maximizes their expected utility [2, 16].

Thus, a rational player aims to maximize the expected utility subject to bounds on the complexity of the strategies that may be used [42]. It is important to note that this assumption is subject to the limited cognitive [49] and computational [29] capabilities that players possess as human beings.

There are cases in which players must make decisions under uncertainty. In games of deterministic perfect information the players knows exactly what is going on in each step of the game [6]. In contrast, games like bridge, poker and blackjack are considered more complex because the players are, to some extent, kept in the dark [6] e.g., due to a lack of information regarding the moves of other players.

In this study, we implement a blackjack game to examine players' decision process under uncertainty (as uncertainty is typically present in real life decision making). Their decisions are classified – based on rationality analysis – into rational (i.e., utility maximization) and irrational behaviors. We characterize the rational and irrational behaviors using factors drawn from personal traits theory.

Personality Traits

A trait is defined as a "disposition to behave in a particular way, as expressed in a person's behavior over a range of situations [46]." For example, an individual who is described as "kind" tends to act kindly, even when there is no pressure or reward for doing so. It summarizes many situations where this person acted kindly, and moreover, it enables us to predict the future behavior of this individual [46]. Traits can serve to predict a person's job performance [24], or the response of a patient to therapy [37].

Denote a specific individual by *i*. An underlying assumption is that there is a direct correspondence between i's possession of a trait T and *i*'s performance of T-related actions. *i* is described as high on T when *i* shows a tendency to constantly behave in this way. Conversely, *i* is described as low on T when *i* shows less tendency to behave in this way. For example, an outgoing individual is "high on extraversion", while an inconsiderate individual may be "low on conscientiousness". An individual who reports a low level of trait-related behavior on a personality traits test is assumed to possess low levels of the given trait [46].

Trait studies provide evidence that people's personality traits are stable over time and across situations. Traits differ from transient internal conditions. The former relate to stable dispositions, and the latter relate to temporary emotional states, such as mood states [37]. Traits maintain a core of consistency that defines an individual's "true nature" [36]. A fundamental model merging the most consensual views among researchers is known as the Five Factor model (OCEAN), composed of five basic traits [46], as follows:

• Openness to experience in life

•Conscientiousness, which describes goal-directed behavior and impulse control in a sociable manner

• Extraversion, which summarizes interpersonal traits

• Agreeableness, which recapitulates traits that capture what people do with and to each other

• Neuroticism, which contrasts emotional stability with a broad range of negative feelings such as anxiety, sadness, irritability and nervous tension, where each subsumes multiple characteristics.

The Five Factor model is based on analyzing the words that ordinary individuals use to describe people's personalities. Individuals rate themselves or others on a wide variety of characteristics sampled from the dictionary [46]. These characteristics reflect the basic way in which individuals comprehend themselves and others in everyday life. Some characteristics are merely descriptors that represent the way an individual tends to act, while others apply to psychological qualities, such as mental structures or processes that may influence the behavior of an individual [46]. To determine which traits go together, the ratings are factor-analyzed. The Five Factor model is considered one of the most accurate models in describing individuals' behavior. Hence, we use it to characterize individuals' behaviors as rational or irrational.

Impulsivity Trait

Impulsivity is a significant personality characteristic that appears in every major system of personality [62]. Especially, in the Five Factor model, three of the factors capture some aspects of impulsivity. For instance, low self-control is measured by the Impulsiveness facet of the Neuroticism domain and by the Self-discipline facet of the Conscientiousness domain.

Impulsivity plays an important role in understanding and identifying different forms of psychopathology [28, 62]. Various scholars provide different definitions of the impulsivity trait. A distinction between "impulse" and "impulsivity" has been presented by (Stanford & Barratt, 1992). Whereas impulse refers to thoughts, impulsivity refers to "a constellation of repeated behaviors that are somehow related to these thoughts" [40]. An impulsive individual is described as a person who has a lack of control over thoughts and behaviors [4].

In his clinical experiments, Barratt discovered three sub-traits where patients seem to be impulsive: motor responses, non-planning ahead and attentional (i.e., changing a cognitive "set") [5, 40]. He found that highly-impulsive patients tended to be inefficient in performing perceptual-motor tasks and had problems with "planning ahead" on laboratory tasks [40]. These three sub-traits are known as the Barratt Impulsiveness Scale (BIS), a self-report inventory of impulsive personality characteristics. Studies reveal that visual augmenters evoked responses from highly-impulsive patients. In this study, one of the subjects' trait we examine is impulsiveness.

Motivation

Another important characteristic that is related to personality traits and has an effect on behavior is the concept of motivation [7, 48]. Motives are the components of motivation that indicate specific types of behavior. They possess two main properties: activating and directing behavior that is based on drive stimuli that impel action [39].

Motives are divided into primary and secondary drives, or alternatively innate and acquired drives. Primary drives are physiological drives that do not require learning processes, such as hunger, thirst and pain, whereas secondary drives are non-physiological drives that are acquired through experience, such as anxiety, fear and ambition [39]. Drives accelerate the individual's response to specific cues in a stimulus situation. Cues are response determinants. They can govern the following three features: when the individual will respond, where the individual will respond and which response the individual will make [39].

Repetition of the individual's response depends on whether there is a reward. Rewards, which can be either extrinsic (e.g., money) or intrinsic (e.g., feeling of relief from pain), are events that strengthen the connection between the stimulus pattern (drives and other cues) and the response [39]. In this study we use motives to influence subjects' behavior. The use of motivation may enhance changes in individuals' patterns of behaviors.

Time constraints

An important influential factor on subject behavior is time pressure. Time pressure is defined as the "time constraint placed on a task that makes people feel time pressured [33]." MacGregor states that decisions under time pressure occur within a time frame with a given deadline that may be imposed by an individual, or established by the external context in which the behavior occurs.

Studies of judgment under time pressure indicate that decision makers give more weight to negative information, which is also interpreted as more risk-avoidant behavior. Decision makers demonstrate a tendency to use a smaller number of attributes and give them greater weight, and increasingly use many pieces of information in a shallower way. Decision makers use non- compensatory decision rules over compensatory decision rules more frequently, especially under severe time constraints. The tendency of locking in on a strategy increases under time pressure, whereas the ability to find alternative strategies in problem solving decreases. In addition, the effects of time constraints can be weakened by payoff and motivation [13].

Time constraints increase the level of arousal and psychological stress during the decision making process. A decision maker may make a decision without taking into account all available alternatives [64]. This is the result of a decrease in searching and processing of information. For instance, under severe time constraints, the accuracy level is reduced and information is processed more rapidly than under no time pressure [13]. Decision makers tend to forget information and to make mistakes in judgment and evaluation [64]. On average, decision makers under severe time constraints make a rapid, incomplete evaluation of all alternatives that may help reach a decision, instead of a complete evaluation of a small subset of alternatives [26].

In addition, time constraints have effects on the framing of decisions. A decision frame represents an individual's schema of a decision problem. The framing effect can be detected by using an eye-tracking device to explore the differences in cognitive effort under both positive and negative framing conditions [30]. Different decision frames can be induced from the same factual information [54]. It only takes a minor change in the framing of a problem to induce different behavior.

People's behaviors in the context of time constraints were examined by comparing a task with and without a time limit. Most laboratory studies conceptualize time constraints as a condition in which an individual will choose a steady-state strategy for handling a decision task, which differs from the strategy that the individual would use if no time limit was imposed [33]. In this study we apply time constraints to decision making, to expose behavioral patterns.

Gender

The models of personality express that men and women differ in their biologically and evolutionarily based innate temperament and hormonal differences [61]. For instance, [20] found that women have proportionally larger Wernicke and Broca language-associated regions of the cerebral cortex than men. They suggest that these anatomical differences may correlate with the superior language skills previously demonstrated in women.

The existence of gender differences was demonstrated in relation to personality characteristics. Findings show that women score higher than men in agreeableness and emotional expression, while they score lower in emotional stability versus hostility. Conversely, men score higher in extroversion than women [61]. Statistically speaking, findings reveal that women are less impulsive than men. In contrast, individual behavior associated with impulsiveness may have higher prevalence rates in women [27].

Experiments demonstrate that gender-related differences have effect in competitive environments. For instance, in their paper, [17] showed that women may be less effective than men in competitive environments, even if they are able to perform similarly in noncompetitive environments. In the context of stress responses, women tend to be more physiologically reactive to social rejection challenges, while men react more to achievement challenges [53]. Gender differences are considered in this study as well.

To summarize, our experiments are designed to confirm automatic game-based determination of (a) rational vs. irrational personality traits; and (b) impulsiveness trait. These are examined with respect to (a) motivation; (b) time constraints; and (c) gender.

RESEARCH METHODOLOGY

Our methodology is empirical. Initially, subjects complete standardized questionnaires for Big Five personality traits and impulsivity. Then, they participate in a series of experiments via a controlled simulation of blackjack play. We have created a game that extracts traits based on the user's pattern of behavior. We validate the game through standardized questionnaires with a statistically significant subject group, and eventually utilize the validated game to extract traits from new subjects.

The use of questionnaires in relation to a gambling play (e.g., blackjack) is already studied to some extent in the literature. For instance, [60] demonstrated positive relation between individual differences (e.g., impulsivity and sensation seeking) and risky betting behavior in blackjack game. In a similar vein, [35] examined impulsive individuals reaction to risky decision making in Iowa Gambling Task under the impact of reward and punishment. However, unlike former studies, our method views the blackjack card-game as a tool for extracting users' traits to build personality-based user models. The method is broader than using one specific game or another. In similarity to implementing blackjack play, we could have used some other validated game with some other rules.

Participants

194 participants took part in our experiment, of which 53% were women and 47% were men. The participants were chosen randomly, and no reward was offered to them for their participation. Approximately 40% of the respondents were between 26 to 30 years of age. Over 90% of the participants possess post high school education. The average earning level of subjects was above the average in the general population.

Experiment and Tools

First, in order to derive personality traits of players, we used the Big Five Inventory (BFI), a self- report questionnaire in which individuals rate themselves. Each of the five trait dimensions has a scale with a high/low score described by adjectives that characterize the high/low scorer [46]. The questionnaire consists of 44 short statements describing characteristics of people. The participants were asked to rate themselves using a rating scale. The responses were given on a 5-point Likert scale, ranging from 1 – "strongly disagree" to 5 – "strongly agree".

Second, the Barratt Impulsiveness Scale inventory (BIS-11) [5] was performed in order to derive impulsiveness sub traits. The BIS is a self-report questionnaire designed to measure the impulsiveness of the participants. The questionnaire consists of 30 items classified into three sub-scales: motor, non-planning and attentional impulsiveness. All items are answered on a four-point scale: "rarely", "occasionally", "often" and "almost always". "Almost always" indicates the most impulsive response [44]. The level of impulsiveness is derived from the total points for all items. "The higher the summed score for all items, the higher the level of impulsiveness" [44]. The impulsiveness scale questionnaire and the classified items to sub-scales are presented in [44].

Third, the participants were asked to fill in a personal details questionnaire in order to assist in statistically analyzing the results. The questionnaire was composed of five categories: gender, age, earning degree, education and profession. In each category, the participants were given a number of options from which to choose.

Forth, we designed a computer simulation to mimic a situation of a real game in order to study decision making under controlled conditions. We developed a simulation of a card game known as Blackjack or 21. Blackjack is a game of chance and strategy in which a player competes against the dealer or the "house" [15]. We implement a randomized device in the form of a software program that arranges the cards in a random order such that the cards have an equal probability in every possible ordering [56]. The aim of the game is to accumulate cards that add up to 21 or come close to 21 points, and that are higher than the dealer's cards, without going over 21. Blackjack was selected because it is a casino game that involves active decision making by the player and gives him or her the possibility of using information [19] and exercising skill in play to increase the likelihood of desirable outcomes [59].

Blackjack is a sequential game, where the human player p moves first and makes his decisions. When p is done, the dealer plays its move. In the experiment, there were a series of individual blackjack games. The rules were the same in each game. [1] In addition, the players were informed that they may get a bonus during the simulation to increase their motivation to take part in the game. The rules were for single-deck blackjack, as dealt in Las Vegas with slight modifications. The dealer stands on a soft 17. The player may double on any two initial cards, but not after splitting pairs. A game with these rules is an even game with zero edge for the "house" [63]. In our simulation, the option of splitting pairs was not available to make the game easier to understand for an inexperienced player.

In each game, a player starts by placing a bet. She is given an initial amount, a minimum and maximum betting amounts, which are 18,637, 100, and 400, respectively. Afterwards, the dealer deals two cards face up to the player, and then one card face up and another face down (a "hole" card) for itself. In case the dealer's up card is an ace, the player has to decide whether to take insurance.

Later on, the player has to choose her way of action: double down, hit, stand or surrender. In the second stage, she has to decide whether to stand or to take an additional card. This stage can be repeated a number of times.

We analyze the players' decisions through the basic strategy chart. The *basic strategy* is the optimal strategy to play a blackjack hand in every possible situation on the first round after a shuffle [63][2]. The optimal strategy has the maximized mathematical expectation value among the optional strategies. In this experiment, following the basic strategy – choosing the optimal strategy - indicates rational behavior, while deviating from the basic strategy is considered irrational behavior. The player's strategies and outcomes are depicted in Figure 2.

The basic strategy can be either total or composition-dependent [63]. Total dependency means that the decision rules require information regarding the dealer's up card and the sum of points in the player's hand. Composition dependency means that the decision rules require information regarding the dealer's up card and the exact cards that make up the player's hand [63]. For example, a total-dependent strategy recommends to hit on the sum of 12 against a sum of three, whereas a composition-dependent strategy for a sum of 12 against a sum of three requires that the player specify the card combinations, which could be 10-2, 5-7, 2-4-2-4 and so on. If the player has 12 points using a combination of 10-2, and only one deck is being used, the strategy dictates that the player should hit. But if the player has 12 using an 8-4 combination the player should stand. There are minor differences between the composition-dependent and the total-dependent strategies for a single deck [63]. In this study, the analysis was based on a combination of both strategies. To calculate the composition-dependent strategy, we used the charts provided by Peter Griffin in his book *The Theory of Blackjack*. We used the total-dependent strategy for situations when the player was dealt his or her first two cards, and the player must choose a strategy from a set of four strategies. In our simulation, the composition-dependent strategy was designated for situations when the player has three cards or more.

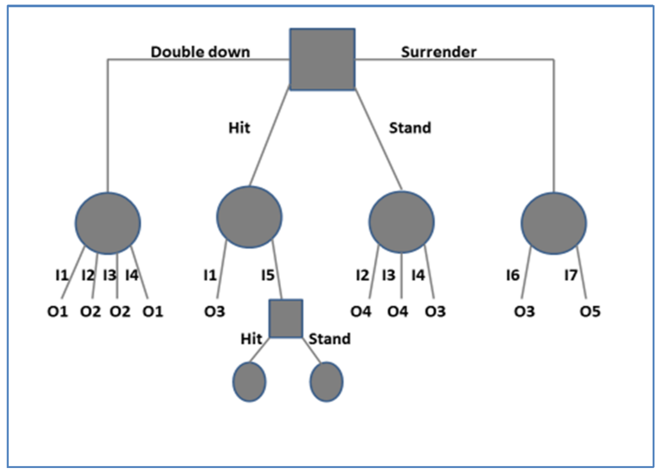

Figure 2. Blackjack Strategies

I1 The player exceeds 21 points

I2 The dealer exceeds 21 points

I3 The player's total points is higher than the dealer's total
I4 The dealer's total points is higher than the player's total
I5 The player's total points is less than 21 points

I6 The dealer has a blackjack

I7 The dealer does not have a blackjack

O1 The player loses twice his or her initial bet amount

O2 The player wins twice his or her initial bet amount

O3 The player loses his or her initial bet amount

O4 The player wins an amount equal to her initial bet

O5 The player loses half of her initial bet amount

In addition, Edward Thorp proved in The Mathematics of Gambling [56] why a player should never take insurance when using basic strategy. As mentioned, a blackjack hand is composed of an ace and 10- point cards. Let's suppose that a player makes a $1 bet and is dealt a 7 and a 5, and the dealer is dealt an ace and a hole card. The dealer asks the player whether he or she wants insurance. The player places an insurance bet of $0.50. If the dealer has blackjack, he

[1] The rules of the game are taken from the book *Basic Black- jack* by Stanford Wong pp: 18-33.

[2] We used the charts given by Peter Griffin in his book *The Theory of Blackjack* pp: 173-178.

pays the player $1; otherwise, the player loses his $0.50. A full single deck has 52 cards, which includes 16 10-point cards and 36 non-10-point cards. The orderings of the cards have equal probability, which means that the hole card has an equal probability to be each one of the 49 cards left in the deck. Therefore, the player's expectation is: (33/49)*(-1/2) + (16/49)*(1) = -1/98. The player's expectation is computed by multiplying each possible gain or loss by the probability of that gain or loss, and afterwards summing the two figures [56]. No matter what bet the player takes, the player's expectation is always negative. Therefore, the player should not take insurance [56]. Hence a player who decides to insure his hand exhibits irrational behavior.

Here, we describe two irrational behavior patterns that are known as bad strategies: "Never Bust" and "Mimic the Dealer". These strategies are also examined in our study. The Never Bust strategy refers to a situation in which a player would never hit a hard total of 12 or more. However, the soft standing numbers should be at least 17 [55]. The Mimic the Dealer strategy relates to a state in which a player hits on 16 or less and stands on 17 or more with no reference to the dealer's up card [19]. The player never doubles down or splits pairs [55].

In some of the games we added a visual stopwatch. In the first stage of each game, the player must choose one action from a set of four (stand, hit, double down and surrender). The player is granted 20 seconds to make this decision. Previous studies showed that 20 seconds are sufficient to create medium time pressure [38], when the subject must choose one from a set of four different options. If the player reaches the second stage, he or she probably chose to hit in the first stage, and the sum of points did not exceed 21. In this case, the player has only two alternatives (hitting or standing). At this stage, the player is given 10 seconds to make a decision. As also reported by [38], 10 seconds are sufficient to create medium time pressure when a subject must choose one from a set of two different options. The second stage can continue a number of times until the player choose to stand or the player's point total exceeds 21.

The procedure

To test our hypotheses, we implemented an online two-stage experiment. In the first stage, each participant completes the electronic questionnaires (described above). Then, the player is requested to enter her personal details. The second stage presents the blackjack simulation. Participants receive a detailed explanation of the game's purpose and rules. To ensure that the participant understands the rules, she is given six trial games. The experiment runs a total of 78 games that are divided into two sets of 39 each. The player is not given the exact number to make it difficult for her to compute an exact (optimal) bet by counting games. Figure 3 presents screen shots of the game.

Figure 3. Screen shots of the game

In each of the first 39 games, the cards' combination, meaning the player's two cards and the dealer's up card, are determined in advance. In part of the games, a visual stop-watch is activated to impose time constraints. As time passes with no decision, a warning appears ("Please make your choice"), which is intended to rush the player to make a decision. The player is allowed to deviate from the restricted time only three times. In the fourth case, the player is dismissed from the experiment. In games in which the stopwatch is not visually activated, the time is measured in the background without the player's awareness of it.

The second set of 39 games includes the same cards' combinations as used in the first set. The difference is in the order of the games. Time is measured as in the first set, however games with a stopwatch in the first set are measured at the background, and vice versa. After the first set of games ends and before the second one begins, the player may be granted a bonus as specified in Table 1.

Accumulated amount	New amount (Bonus)	Minimum bet amount	Maximum bet amount
> 18637	No bonus	100	400
<10000	10639	60	230
>10000, <15000	16379	90	350
>15000, <18637	20257	110	435

Table 1. Bonus table

The bonus is granted to stimulate the player's motivation to continue playing, and to enable the player to continue playing in case of substantial loss. It additionally helps to examine whether the player's risk preferences have changed in the second set as compared to the first set of games. This enables us to test behavioral consistency. The experiment ends with an ending message presented to the player.

Research Hypotheses

RH1: We hypothesize that subjects who demonstrate rational and irrational behavior patterns during the simulation will present personality characteristics that coincide with rationality and irrationality.

RH2: We hypothesize that a player who makes decisions in less than average time will demonstrate a higher impulsiveness degree than the average one. In addition, we presume that different results will be generated according to gender.

RH3: We hypothesize that a player who demonstrates an irrational behavior will have an impulsiveness degree higher than the average one.

RH4: We hypothesize that a player who makes decisions under time constraints will demonstrate more irrational behavior compared to decision making with no time constraints.

RH5: We hypothesize that subjects who are granted a bonus between the two sets of 39 games will bet a higher amount (on average) in the second set of 39 games compared to the first roundest of 39 games.

RESULTS

First, we define the irrationality variable that aided in testing our research hypotheses. We distinguish between the different stages in each game and classify the participants' choices in each stage of each game. Second, we present the final results encountered.

The optimal strategy maximizes the expected value and the second-best strategy has the second-highest value. We define an irrationality variable to accurately model deviations from rational behavior. In the first stage of each game, the irrationality variable is assigned values as follows:

-1: The player deviated from the basic strategy

0: The player chose the second-best strategy

1: The player chose the optimal strategy

In the second stage of each game, two strategies remain: "hit" and "stand". If the chosen strategy is the optimal, the choice is rational (and vice versa). The irrationality variable is thus assigned values as follows:

-1: The player deviated from the basic strategy

1: The player chose the optimal strategy

Note that the second stage can be executed a number of times until the player decides to stand or alternatively, exceeds a total of 21 points.

To examine our assumptions, we used statistical methodologies: Pearson's Correlation, and Duncan's multiple range test at a level of significant 0.05. We discovered important insights concerning the behavioral patterns of individuals that relate to the traits, as well as factors that inter-correlate with rational and irrational behaviors. On the other hand, our findings were inconclusive regarding the relationship between decision making under time constraints and irrational behavior.

The first important insight is that irrational behavior patterns are consistent patterns of behavior as rational behavior patterns. We found a close relationship between deviation from the basic strategy in the second stage of the game and insurance taking. In the second stage of the game, the participants had to choose between two opposite strategies: to stand with their current point total or to draw an additional card. An act of deviation from the basic strategy is more apparent in the second stage of the game, when choosing one of the two optional strategies is necessarily considered irrational behavior, if the unchosen strategy is the optimal one. As mentioned in the methodology chapter, a player who decides to insure his or her hand demonstrates an irrational behavior. No matter what bet amount the player makes, his or her expectation is always negative. Therefore, the player should not take insurance [56].

Our findings showed that participants who insured themselves tended to deviate more from the basic strategy in the second stage of the game (P-Value < 0.034) or alternatively, tended to choose less according to the basic strategy. In the second stage of the game (P-Value < 0.009). On the other hand, the participants showed neither rational nor irrational behavior in the first stage of the game. Further, participants maintained the same level of irrationality (i.e., deviation from basic strategy) in both sets of 39 games, regardless of a reward between the sets.

The second important insight was that Neuroticism is one of the Big Five personality factors (Openness to experience, Conscientiousness, Extroversion, Agreeableness and Neuroticism). It contrasts emotional stability with a broad range of negative feelings, such as anxiety, sadness and irritability and nervous tension [46]. In addition, it may predict negative judgment biases [58]. Subjects who score high in their Neuroticism factor possess a hyper-arousal visceral system [58], and hence experience negative feelings more often than people with an average level. For such individuals, feelings such as the following are common: signs of tension or anxiety, expression of guilt, excitability, irritability, seeking of reassurance and placing a greater burden on coping mechanisms [10]. Such individuals possess a higher sensitive behavior inhabitation system (BIS) that scans the environment for stimuli associated with punishment cues or novel stimuli and interrupts ongoing behavior in the presence of such signals, focuses attention on the threatening stimulus (e.g., pictures, sounds) and increases psychological arousal.

Neuroticism is characterized by risk-avoiding behavior [8] and it predicts whether a participant will avoid "big loss". In other words, neurotic subjects find big losses particularly aversive and therefore they will avoid those [58]. Previous studies presented a relationship between Neuroticism and avoiding big losses, but they did not show that Neuroticism predicts winnings, or alternatively, making optimal decisions [58]. In our research, we demonstrated a relationship between Emotional Stability (the opposite pole of the Neuroticism factor) and making optimal decisions.

We identified that the Emotional Stability factor is higher among players who deviated less from the basic strategy in the second stage of the game. Choosing one of the two optional strategies is considered a rational behavior when the chosen strategy is the optimal one. The findings were highly significant (P-Value < 0.0099). Moreover, in games number 9 and 48 in which the player was dealt a 10 and an ace (blackjack) and the dealer's up card was an ace, the Emotional Stability factor was higher (on average) among those who did not insure themselves (P-Value < 0.02). In these games, the only decision the players had to make was whether or not to take insurance.

A full single deck has 52 cards, which includes 16 10-point cards and 36 non-10-point cards. Let's suppose that the player makes a $1 bet, Then, the player expectation is: (34/49)(-1/2) + (15/49)(1) = (-2/49). Hence, the players should not take insurance. This result found that the relationship between rational behavior (i.e., not taking insurance) and the Emotional Stability factor was consistent with the former finding.

Barratt's impulsiveness scale consists of three sub-traits: Attentional key, Non-planning key and Motor key. The Attentional key is defined as "the ability to focus on the tasks at hand and cognitive instability" [62]. Subjects with a high level in their Attentional key act with less forethought than others do, due to difficulty in keeping their attention focused on the task during the time when they are preparing their response [40]. The participants in our research faced a task of choosing the optimal strategy/strategies in each stage of each game. Fulfillment of this cognitive task required that they calculate their strategies' utilities and select the strategy that maximized their utility. Players who scored high in their Attentional key demonstrated difficulty in fulfilling their cognitive task due to lack of attention and cognitive instability. As a result, they deviated more from the basic strategy in the second stage of the game, when only two opposite strategies were optional and therefore the deviation was significantly apparent. However, the players demonstrated neither rational nor irrational behavior in the first stage of the game.

The participants who possessed a higher Attentional key level (on average) demonstrated a higher level (on average) of irrational behavior or alternatively deviated more from the basic strategy in the second stage of the game. The results were highly significant (P-Value < 0.001). In addition, in games number 9 and 48 in which the player was dealt a 10 and an ace (blackjack) and the dealer's up card was an ace, the Attentional key level was higher (on average) among those who insured themselves (P-Value < 0.001). This result found that the relationship between irrational behavior (i.e., insurance taking) and the Attentional key was consistent with the former finding.

Moreover, individuals who presented risk-avoiding behavior possessed a low score (on average) in their Non-planning key sub-trait, regardless of whether their decision was rational or irrational.

The third significant insight displayed that women scored higher in their Attentional and Motor keys sub-traits and presented compatible behavior by responding in less than the average time (with and without time constraints) compared to men. Women also acted in a more irrational manner than men by deviating more from the basic strategy in both rounds. Moreover, no relationship was found between their irrational behavior and receiving a bonus between rounds. On the other hand, men scored higher in their Emotional Stability factor (like in former studies) and demonstrated a more rational behavior pattern than women. This finding coincides with the result that subjects who demonstrated more rational behavior patterns, scored higher in the Emotional Stability factor. Also, they bet higher (on average) in the first and second rounds compared to women. The first round result was significant and the second round result was not.

The double down strategy is considered a risk-taking strategy, unlike the hitting or standing strategies. When the risk for busting is higher than the expectation to win, the loss is doubled. Our findings showed that men took more risks than women (this is consistent with other research). Neither gender presented irrational behavior in choosing to double down during the experiment. This means that the players of different genders who chose to double down demonstrated rational behavior most of the time by choosing to double down in games in which the optimal strategy was indeed to double down. Moreover, the players of different gender who chose to surrender at least once demonstrated rational behavior most of the time by choosing to surrender in games in which the optimal strategy was indeed to surrender.

The fourth meaningful insight presented that incentives (i.e., rewards) have influence on subjects' betting patterns. [31] argues that the meaning of motivation is "the switching on of some pattern of behavior, of a program of action specified within the individual. That program might be innate or it might have been modified by experience." In order to trigger the corresponding pattern of behavior, the appropriate stimulus must be given to the individual [31]. Rewards, which are in our case money, feeling of achievement and loss/gain, are considered incentives that indirectly engage instinctive behavior [31], that is, trigger changes in behavior patterns, such as deviating more or less from basic strategy, betting more or less and so on.

In the beginning of the card-game simulation, the participants received an initial betting amount of 18,637. Some of the participants were granted a bonus after game 39. The bonus was granted, if after game 39, the player accumulated an amount lower than the initial amount; otherwise, no bonus was granted and the player continued with the accumulated amount. The amount of the bonus depended upon the accumulated amount of the player after the 39th game. If it was less than 10,000, the player was granted 10,639, while if it was higher than 10,000, but less than 15,000, the player was granted 16,379. If the amount was less than 18,638 (i.e., the initial amount), but higher than 15,000, the player was granted 20,257. Otherwise, the amount was higher than the initial amount and therefore no bonus was granted.

In general, we found that the difference between the average bet amounts between rounds was higher among players who were granted a bonus (149 players) when compared to players who did not receive a bonus (45 players). The average bet amount was higher in the second round (350) compared to the first round (322). We did not find a relationship between the average bet amount in each round and irrational behavior. In particular, we discovered that each bonus group yielded different betting and behavior patterns. Also, we identified differences in betting and behavior patterns between groups who were granted a bonus and those who did not receive a bonus. In conclusion, rewards triggered feelings of gain or fear from loss, which led to changes in subjects' betting patterns, while they had no significant influence on subjects' behavior patterns, whether rational or irrational.

The fifth insight showed that participants, who acted by the basic strategy and maximized their utility, ended up with financial gains, while participants who deviated from basic strategy ended with financial losses.

In the blackjack literature [19], there are two known irrational behavior patterns: "mimic the dealer" and "never bust". In our research, there were participants who demonstrated these irrational patterns of behavior. We found that the Non-planning key sub-trait was higher (on average) among participants who mimicked the dealer, while it was lower (on average) among participants who presented the latter irrational pattern of behavior. These findings contribute to the identification of irrational patterns of behavior with an impulsiveness sub-trait.

In addition, the Non-planning key sub-trait was higher (on average) among participants who received a bonus in the amount of 16,379. This group demonstrated the highest deviation from the basic strategy (i.e., irrational behavior pattern) in both rounds. In contrast, the Non-Planning key was higher (on average) among players who chose the optimal strategy in the first stage of each game. This finding is compatible with the conclusion that no relationship was found between the Non-planning key and rational/irrational behavior.

In our card-game simulation, a player was given the option to choose whether to double down or surrender in the first stage of each game with no possibility to hit (i.e., to take an additional card) afterwards. The double-down strategy is considered a risk-taking behavior, as the player may lose twice his or her bet amount. In contrast, the surrender strategy is considered a risk-avoiding behavior. The player prefers to lose half of the original bet rather than play and take the chance of losing the original bet amount. We discovered that the average reaction time among players who doubled down at least once was higher compared to those who did not double down. The same result was found concerning the surrender strategy. Players needed more time to reflect on their optional moves and to make their decisions. This finding is compatible with the result that players who chose to surrender, scored lower (on average) in their Non- planning key sub-trait, i.e., players were more settled and less impulsive in their reaction, and therefore it took them more time to make their decision.

CONCLUSIONS AND FUTURE RESEARCH

Psychological personality factors assist in explaining and predicting the behavior of individuals in a systematic, scientific way, and in establishing behavioral patterns. By understanding interrelations among these patterns we can build reliable user models. Reliable user models are instrumental to effective and efficient information delivery to end users. Therefore, it should be beneficial to have a practical method for extracting personality factors. In this paper we present a method that automatically and implicitly reveals the traits of irrationality vs. rationality and impulsiveness vs. non-impulsiveness. These traits can then be applied towards building a comprehensive user model.

In this study, data was collected via experiments, and the results of our analyses was verified via standard self-reports. For example, women demonstrated impulsive behavior both in their observable behavior and in their impulsiveness sub- traits when compared to men. In addition, we were able to reveal various relationships between the traits that characterized each player, the reaction to time constraints and rewards and the actual behavior demonstrated. Our major contribution is thus in the automated and implicit extraction of personality factors and their correlation with rational and irrational patterns of behavior. We thus overcome the need for explicit extraction by questionnaires.

Our method can be developed further by examining additional influential factors such as framing a problem by individuals with different characteristics, the heuristics they use in different situations and the influence of different time constraints and rewards on subjects' with different characteristics. The more information we automatically gather about user behavior patterns and their influential factors, the better equipped we are to build an accurate user model, and in turn provide an effective personalization service.

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