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Decision Support Approach based Rough Sets Theory to Investigate the Relationship between Personality Traits and Drug User (Year-based Definition)

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Abstract: There is no doubt that the use of drugs has significant consequences for society, it introduces risk into the human life, increasing risk of poor health and greater earlier mortality and morbidity. The rapid growth of artificial intelligence and machine learning can provide useful tools for analyzing this problem; various methods have been given by researchers for increasing the prediction rate of drug users. This work proposes a decision support approach to investigate the relationship between drug user (year-based user definition) and personality traits. Psychologists approved the recent personality traits Five Factor Model (FFM) for understanding human individual differences. Two additional factors of personality are proven to be important for analysis of substance use, Impulsivity and Sensation-Seeking. The data of five factor personality profiles, Impulsivity and Sensation-Seeking, in addition to biographical data of 21 different types of legal and illegal drugs are depicted in tabular form and rough sets principles are applied to obtain all reducts and set of generalized rules are extracted to predict the drug user/Non-user (year-based user definition). The resultant set of classification rules performed with basic logic functions can be considered as knowledge base with high accuracy and may be valuable in many applications.

Keywords: Personality Traits; Five Factor Model ; Rules Extraction; Drug Abuse Detection; Rough Sets Theory; Feature Selection.

1 INTRODUCTION

One of the most important issues considering the mental health nowadays is drug addiction, where it can destroy a life and a nation easily. Drug addiction means the taking of various drugs illegally and being addicted to those drugs for their toxic and addictive effects. Drug addiction has become a dangerous fact for which the young generation from all lifestyles is affected silently. Dissatisfaction is the reason for this addiction, Joblessness issues, political upheaval, absence of family ties, and absence of adoration friendship offer ascent to disappointments [1]. Drug is considered to be one of the most consumed psychoactive substances. According to world health organization, every year drug consumption contributes to 3 million deaths across the globe and its harmful use leads to 5.1% of various global diseases [2].

The practical importance of the problem of evaluating an individual's risk of consuming and/or abusing drugs cannot be underestimated [3]. The linking of personality traits to risk of substance use disorder is an enduring problem [4]. Many studies had been done to find the answer of the following Questions: How do personality, gender, education, nationality, age, and other attributes affect this risk? Is this dependence different for different drugs? Which personality traits are the most important for evaluation of the risk of consumption of a particular drug, and are these traits different for different drugs? Is the prediction of drugs usage by a person can be helpful to prevent the individuals from getting addicted to drugs? Also, some related works had been done by researchers on drugs and addiction predictions to improve the methods which are used. Bergh [5] proposed an approach to Predicting Alcohol Consumption in Adolescents from

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Historical Text Messaging Data. Belcher, et al. [6][studied the personality traits and vulnerability or resilience to substance use disorders. Weissman, et al. [7] studied earlier adolescent substance use onset predicts stronger connectivity between reward and cognitive control brain networks. Andreassen, et al. [8] studied the relationships between behavioral addictions and the five-factor model of personality. In this work all the questions which posed above have been reformulated as classification problems and a well-known data mining technique depend on rough set theory have been employed to address these problems and extracting classification rules to predict the Drug User/Non-User (year-based user definition).

2 RESEARCH PROBLEM

Psychologists tried many times to identify the relationship between personality traits and drug user/Non-user. Many studies are done and data mining techniques and methodologies have been used to address these issues such as decision trees, linear discriminant analysis, and probability density function estimation using radial basis functions [9]. The main aim of this work is to find answers to these questions: Which personality traits are the most important for evaluation of the risk of abusing drugs, and are these traits different for different drugs? How do personality, gender, education, nationality, age, and other attributes affect this risk of abusing drugs? Is this dependence different for different drugs?

2.1 PERSONALITY TRAITS

In recent years and due to the development in scientific research, the psychologists approved the recent personality traits Five Factor Model (FFM) for understanding human individual differences [9]. It is consists of Neuroticism (N), Extraversion (E), Openness to Experience (O), Agreeableness (A), and Conscientiousness (C). Where these traits can be defined as follow:

–N : "Neuroticism is a long-term tendency to experience negative emotions such as nervousness, tension, anxiety and depression (associated adjectives [10]: anxious, self-pitying, tense, touchy, unstable, and worrying)

–E: " Extraversion manifested in characters who are outgoing, warm, active, assertive, talkative, and cheerful; these persons are often in search of stimulation (associated adjectives: active, assertive, energetic, enthusiastic, outgoing, and talkative)

–O: "Openness to experience is associated with a general appreciation for art, unusual ideas, and imaginative, creative, unconventional, and wide interests (associated adjectives: artistic, curious, imaginative, insightful, original, and wide interest)

–A : "Agreeableness is a dimension of interpersonal relations, characterized by altruism, trust, modesty, kindness, compassion and cooperativeness (associated adjectives: appreciative, forgiving, generous, kind, sympathetic, and trusting)

–C: "Conscientiousness is a tendency to be organized and dependable, strong-willed, persistent, reliable, and efficient (associated adjectives: efficient, organised, reliable, responsible, and thorough)"

The values of the five factors (N, E, O, A, C) are used as inputs in numerous statistical models for prediction, diagnosis, and risk evaluation. These models are employed in psychology, psychiatry, medicine, education, sociology, and many other areas where personality may be important. Other twoadditional characteristics of personality are proven to be important for analysis of substance use, Impulsivity (Imp) and Sensation-Seeking (SS) [11].

–Imp:" Impulsivity is defined as a tendency to act without adequate forethought"

–SS: "Sensation-Seeking is defined by the search for experiences and feelings, that are varied, novel, complex and intense, and by the readiness to take risks for the sake of such experiences"

2.2 ROUGH SETS THEORY

Rough sets theory (RST) is the core of the most recent approximations based mathematical model to deal the imprecision and uncertainty present in knowledge [12–16], as well as extract decision rules which acts as classification scheme for prediction. We can say that it is a tool for database mining or knowledge discovery in relational databases. It is a formal approximation of a crisp set defined by its two approximations namely, Upper and Lower approximation [17] as shown in fig. 1.

The indiscernible relation IND(B) can be defined as:

$$IND(B) = \{(x,y) \in U : \text{for all } a \in B, a(x) = a(y)\} \tag{1}$$

Also, In decision system (U,A) let $B \subseteq A$ and $X \subseteq U$, the lower approximate $\underline{B}(x)$, upper approximate $\overline{R}(x)$ and the boundary of X denoted by BND(X) are defined as follows:

$$\underline{B}(x) = \{x \in U : [x]_B \subseteq X\} \tag{2}$$

$$\overline{B}(x) = \{x \in U : [x]_B \bigcap X \neq \Phi\} \tag{3}$$

$$BND(X) = \overline{B}(x) - \underline{B}(x) \tag{4}$$

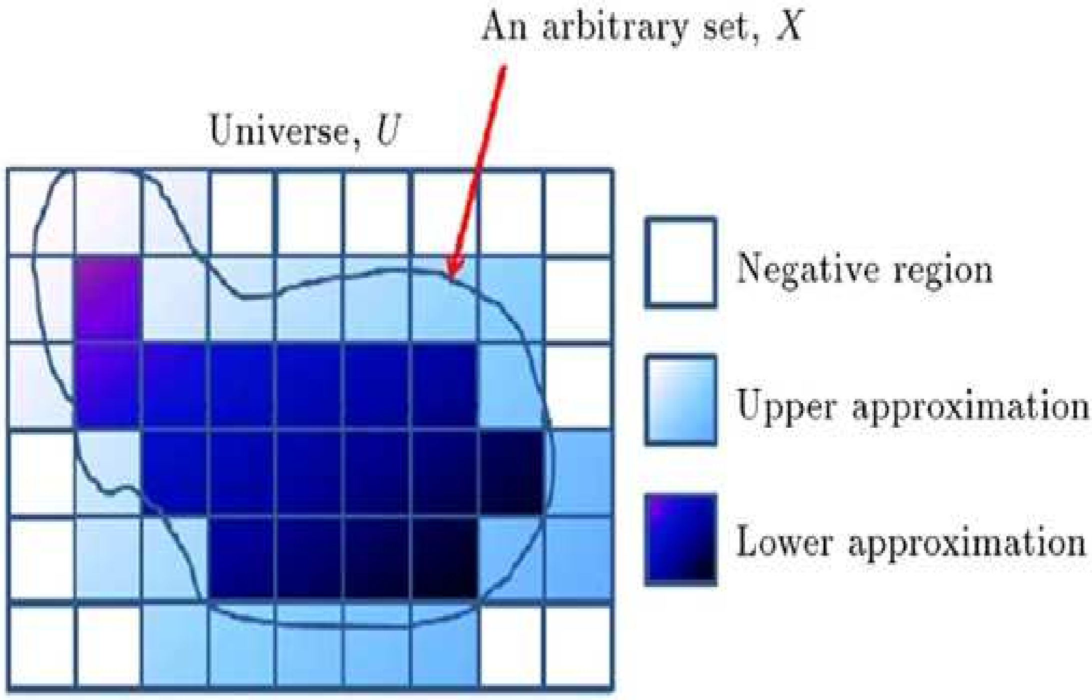

Fig. 1: Representation of a set approximation of an arbitrarily set X in U

The B-positive region of X and The B-negative region of X , denoted as $POS_B(X)$ and $NEG_B(X)$ respectively can be defined as :

$$POS_B(X) = \overline{BX} \tag{5}$$

$$NEG_B(X) = U - \overline{BX} \tag{6}$$

The accuracy of approximation can be written as:

$$\alpha_B(X) = \frac{|\underline{BX}|}{|\overline{BX}|} \tag{7}$$

Where $|x|$ denotes the cardinality of X. Obviously $0 \leq \alpha_B(X) \leq 1$. The rough membership function can be written as

$$\mu_X^B(x) = \frac{|X \bigcap [x_i]_{Ind(B)}|}{|[x_i]_{Ind(B)}|} \tag{8}$$

Obviously

$$\mu_X^B(x) \in [0,1] \tag{9}$$

3 ANALYSIS

In the life of the any human there are various factors (attributes) for addiction that leads to increase the probability of drug consumption. Some of these attributes correlated with psychological, social, environmental, and economic characteristics [18,19]. The most important risk factors are likewise associated with personality traits [20]. So this study proposes a methodology based on rough set theory to extract a decision rules for predicting drug user/ non use r(year-based user definition). We defined different categories (classifications) of drug users based on the regency of use as follow: class of ”non-users”, ”year-based, month-based and week-based user/non-user. Data had been taken from The database which was collected by Elaine Fehrman [21] for 21 different types of legal and illegal drugs separately, where the values of the five factors (N, E, O, A, C) in addition to Impulsivity (Imp) and Sensation-Seeking (SS) as well as biographical data: age, gender, and education are used as the conditional attributes in the decision table shown in Table 1.

Linear discriminates for user/non-user separation is evaluated by several methods, here we will consider the following Relations:

For users $$Th + \sum k_i CT > 0 \tag{10}$$

Table 1: Decision table of coefficients of linear discriminant for user/non-user (year-based user definition)

	TH	Age	Gndr	Edu	N	E	O	A	C	Imp	SS	Drug
x1	0.218	0.585	0.241	0.342	0.228	0.101	0.133	0.031	0.165	0.211	0.575	Alcohol
x2	0.543	0.643	0.293	0.249	0.063	0.176	0.347	0.103	0.201	0.241	0.418	Amphetamines
x3	0.527	0.647	0.507	0.085	0.124	0.075	0.036	0.249	0.142	0.191	0.420	Amyl nitrite
x4	0.296	0.272	0.282	0.263	0.594	0.110	0.437	0.187	0.007	0.102	0.419	Benz
x5	0.130	0.569	0.245	0.310	0.069	0.190	0.521	0.020	0.194	0.034	0.411	Cannabis
x6	0.169	0.259	0.367	0.217	0.036	0.168	0.575	0.064	0.236	0.571	0.072	Chocolate
x7	0.494	0.685	0.280	0.007	0.211	0.177	0.077	0.247	0.175	0.086	0.521	Cocaine
x8	0.517	0.323	0.063	0.129	0.305	0.469	0.039	0.061	0.602	0.079	0.434	Caffeine
x9	0.973	0.153	0.682	0.408	0.257	0.014	0.090	0.060	0.079	0.346	0.376	Crack
x10	0.464	0.782	0.275	0.101	0.015	0.099	0.238	0.025	0.173	0.004	0.453	Ecstasy
x11	0.849	0.584	0.378	0.168	0.352	0.252	0.222	0.275	0.014	0.216	0.359	Heroin
x12	0.675	0.790	0.392	0.033	0.070	0.046	0.214	0.075	0.189	0.038	0.354	Ketamine
x13	0.432	0.656	0.342	0.212	0.035	0.134	0.370	0.054	0.129	0.026	0.481	Legal highs
x14	0.685	0.757	0.288	0.128	0.112	0.137	0.451	0.001	0.040	0.015	0.302	LSD
x15	0.527	0.450	0.360	0.322	0.244	0.331	0.495	0.246	0.051	0.050	0.289	Methadone
x16	0.573	0.712	0.310	0.197	0.106	0.119	0.490	0.033	0.053	0.040	0.293	MMushrooms
x17	0.149	0.579	0.209	0.446	0.096	0.076	0.345	0.017	0.255	0.011	0.472	Nicotine
x18	0.847	0.859	0.247	0.111	0.268	0.002	0.087	0.032	0.095	0.016	0.315	VSA
x19	0.368	0.601	0.333	0.190	0.176	0.088	0.299	0.267	0.169	0.092	0.506	Heroin pleiad
x20	0.230	0.576	0.261	0.296	0.062	0.222	0.512	0.077	0.185	0.013	0.396	Ecstasy pleiad
x21	0.069	0.449	0.271	0.284	0.292	0.119	0.429	0.207	0.156	0.073	0.537	Benz. pleiad

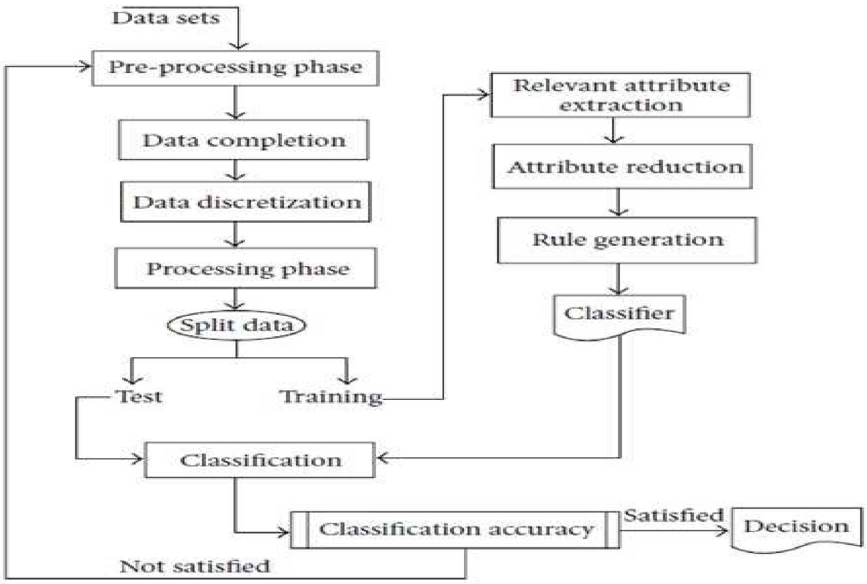

Fig. 2: The overall steps of the suggested rough sets methodology

For non users $$Th + \sum k_i CT \leq 0 \qquad (11)$$

where

Th : is the threshold.

CT : is the conditional attributes.

k_i : are coefficients of the conditional attributes.

Now, we will use rough sets methodology to discover structural relationships within the given data to obtain all reducts and finally a set of generalized classification rules are extracted to predict the drug user/non-user. The overall steps of the suggested rough sets methodology are shown in fig. 2.

By using RST analysis toolkit software called ROSETTA where Semi-Naive algorithm were used to

Table 2: The discretized decision table of Table 1.

	TH	Age	Gndr	Edu	N	E	O	A	C	Imp	SS	Drug
x1	[0.194, 0.224)	[-0.593, -0.584)	[0.152, 0.304)	[0.236, *)	[-0.266, -0.170)	[0.100, 0.139)	[*, -0.084)	[-0.031, -0.028)	[-0.167, -0.160)	[-0.391, -0.201)	[0.556, *)	Alcohol
x2	[-0.558, -0.535)	[-0.645, -0.622)	[-0.301, -0.290)	[-0.256, -0.233)	[0.050, 0.067)	[-0.183, -0.172)	[0.346, 0.359)	[-0.145, -0.090)	[-0.218, -0.197)	[0.229, 0.294)	[0.415, 0.419)	Amphetamines
x3	[-0.535, -0.510)	[-0.651, -0.645)	[-0.594, -0.449)	[0.059, 0.107)	[0.110, 0.150)	[0.061, 0.087)	[-0.084, 0.002)	[-0.258, -0.248)	[-0.149, -0.135)	[-0.201, -0.112)	[0.420, 0.427)	Amyl nitrite
x4	[-0.332, -0.182)	[-0.297, -0.265)	[-0.285, -0.281)	[-0.273, -0.256)	[0.473, *)	[-0.114, -0.099)	[0.433, 0.444)	[-0.197, -0.145)	[-0.029, 0.004)	[0.097, 0.159)	[0.419, 0.420)	Benz.
x5	[0.031, 0.140)	[-0.572, -0.509)	[-0.246, -0.227)	[-0.316, -0.303)	[-0.087, -0.065)	[-0.206, -0.183)	[0.517, 0.548)	[-0.022, -0.018)	[-0.197, -0.191)	[-0.112, -0.030)	[0.404, 0.415)	Cannabis
x6	[0.159, 0.194)	[-0.265, -0.206)	[0.304, *)	[-0.233, -0.214)	[0.011, 0.050)	[-0.172, -0.152)	[0.548, *)	[0.033, *)	[-0.245, -0.218)	[*, -0.391)	[*, 0.181)	Chocolate
x7	[-0.510, -0.479)	[-0.698, -0.670)	[-0.281, -0.277)	[-0.054, 0.013)	[0.194, 0.228)	[0.139, 0.323)	[0.058, 0.082)	[-0.248, -0.246)	[-0.180, -0.174)	[0.083, 0.089)	[0.514, 0.529)	Cocaine
x8	[0.374, *)	[-0.386, -0.297)	[-0.073, 0.152)	[0.107, 0.236)	[*, -0.266)	[0.323, *)	[0.002, 0.058)	[-0.068, -0.060)	[*, -0.428)	[0.076, 0.083)	[0.427, 0.444)	Caffeine
x9	[*, -0.911)	[-0.206, *)	[*, -0.594)	[-0.427, -0.365)	[0.251, 0.263)	[-0.045, -0.006)	[0.089, 0.152)	[-0.060, -0.057)	[-0.087, -0.066)	[0.294, *)	[0.368, 0.386)	Crack
x10	[-0.479, -0.448)	[-0.786, -0.769)	[-0.277, -0.273)	[-0.106, -0.054)	[-0.025, 0.011)	[0.087, 0.100)	[0.230, 0.269)	[-0.028, -0.022)	[-0.174, -0.171)	[-0.009, 0.004)	[0.444, 0.463)	Ecstasy
x11	[-0.911, -0.848)	[-0.584, -0.581)	[-0.385, -0.369)	[-0.179, -0.148)	[0.322, 0.473)	[-0.291, -0.237)	[0.218, 0.230)	[*, -0.271)	[0.004, 0.027)	[0.159, 0.229)	[0.357, 0.368)	Heroin
x12	[-0.680, -0.624)	[-0.824, -0.786)	[-0.449, -0.385)	[0.013, 0.059)	[0.067, 0.083)	[0.024, 0.061)	[0.152, 0.218)	[-0.076, -0.068)	[-0.191, -0.187)	[0.026, 0.039)	[0.335, 0.357)	Ketamine
x13	[-0.448, -0.400)	[-0.670, -0.651)	[-0.351, -0.337)	[-0.214, -0.204)	[-0.048, -0.025)	[-0.135, -0.126)	[0.359, 0.400)	[-0.057, -0.043)	[-0.135, -0.112)	[-0.030, -0.021)	[0.477, 0.494)	Legal highs
x14	[-0.766, -0.680)	[-0.769, -0.734)	[-0.290, -0.285)	[-0.148, -0.119)	[-0.170, -0.109)	[-0.152, -0.135)	[0.444, 0.471)	[-0.008, 0.033)	[0.027, *)	[-0.015, -0.009)	[0.298, 0.309)	LSD
x15	[-0.535, -0.510)	[-0.509, -0.449)	[-0.369, -0.351)	[-0.365, -0.316)	[0.228, 0.251)	[*, -0.291)	[0.493, 0.504)	[-0.246, -0.226)	[-0.052, -0.029)	[0.045, 0.062)	[0.181, 0.291)	Methadone
x16	[-0.624, -0.558)	[-0.734, -0.698)	[-0.321, -0.301)	[-0.204, -0.193)	[-0.109, -0.087)	[-0.126, -0.114)	[0.471, 0.493)	[-0.043, -0.032)	[-0.066, -0.052)	[0.039, 0.045)	[0.291, 0.298)	MMushrooms
x17	[0.140, 0.159)	[-0.581, -0.577)	[-0.227, -0.073)	[*, -0.427)	[0.083, 0.110)	[-0.082, -0.045)	[0.322, 0.346)	[-0.018, -0.008)	[-0.428, -0.245)	[0.004, 0.012)	[0.463, 0.477)	Nicotine
x18	[-0.848, -0.766)	[*, -0.824)	[-0.254, -0.246)	[-0.119, -0.106)	[0.263, 0.280)	[-0.006, 0.024)	[0.082, 0.089)	[-0.032, -0.031)	[-0.112, -0.087)	[-0.021, -0.015)	[0.309, 0.335)	VSA
x19	[-0.400, -0.332)	[-0.622, -0.593)	[-0.337, -0.321)	[-0.193, -0.179)	[0.150, 0.194)	[-0.099, -0.082)	[0.269, 0.322)	[-0.271, -0.258)	[-0.171, -0.167)	[0.089, 0.097)	[0.494, 0.514)	Heroin pleiad
x20	[0.224, 0.374)	[-0.577, -0.572)	[-0.266, -0.254)	[-0.303, -0.290)	[-0.065, -0.048)	[-0.237, -0.206)	[0.504, 0.517)	[-0.090, -0.076)	[-0.187, -0.180)	[0.012, 0.026)	[0.386, 0.404)	Ecstasy pleiad
x21	[-0.182, 0.031)	[-0.449, -0.386)	[-0.273, -0.266)	[-0.290, -0.273)	[0.280, 0.322)	[-0.126, -0.114)	[0.400, 0.433)	[-0.226, -0.197)	[-0.160, -0.149)	[0.062, 0.076)	[0.529, 0.556)	Benz. pleiad

Table 3: Reducts of discretized decision table.

Reduct	{TH, E }	{Imp }	{ Age }	{N}	{O}	{C}	{SS}	{Gndr}	{A}	{Edu}
Support	100	100	100	100	100	100	100	100	100	100
Length	2	1	1	1	1	1	1	1	1	1

discretize the data in table 1 to be as shown in Table 2 where * means do not care condition. In the Next step reduction techniques based rough sets is used to determine the minimal reducts of attributes that can characterize all the knowledge in the decision tables as shown in Table 3. Finally, the knowledge gained from all extracted reducts can be outlined by rough sets dependency rules as shown in Table 4. As shown in Table 4, the extracted decision rules represent the impact of the personality traits on the risk of drug consumption. It is found that the risk of drug consumption increase as the values of N and O increase , while the risk decreases as an increase in the values of A and C. So we can conclude that drug users (year-based user definition) have higher values of on N and O, and lower on A and C when compared to drug non-users(year-based user definition). The impact of the values of E is cannot be generalized i.e. specific. Also, all drugs can be separated into eight groups according to the values which differ from the sample mean for groups of users for the year-based user/non-user as shown in Table 5.

In order to check the effectiveness of the proposed method and test the accuracy of the obtained results, our results for are compared with those of Fehrman [22] and it is clear that there is an excellent agreement.

4 CONCLUSION

This work used the principles of rough set theory to find and explain the relationship between drug use and personality traits, impulsivity, and sensation seeking, by generating a set of decision rules to investigate and predict the impact of the personality traits on drug user/Non-user (year-based user definition) . It is concluded that high N, high O, low A, and low C are the most common personality correlates of drug use. The suggested methodology has simplified logic-based rules required to effectively analysis of drug abuse, constructs a knowledge base with high accuracy and may be valuable in many applications. The future work will be extending by using other intelligent systems like neural networks, genetic algorithms, fuzzy approaches, and so forth.

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CONFLICTS OF INTEREST

There are no conflicts of interest declared by the authors for the publication of this paper.

Table 4: The set of generated rules

Rule	LHS Support	RHS Support	RHS Accuracy	LHS Coverage	RHS Stability
If Imp([-0.391, -0.201)) ⇒ Drug (Alcohol)	1	1	1.0	0.047619	1.0
If Imp([0.229, 0.294)) ⇒ Drug (Amphetamines)	1	1	1.0	0.047619	1.0
If Imp([-0.201, -0.112)) ⇒ Drug (Amyl nitrite)	1	1	1.0	0.047619	1.0
If Imp([0.097, 0.159)) ⇒ Drug (Benz.)	1	1	1.0	0.047619	1.0
If Imp([0.045, 0.062)) ⇒ Drug (Methadone)	1	1	1.0	0.047619	1.0
If Imp([0.039, 0.045)) ⇒ Drug (MMushrooms)	1	1	1.0	0.047619	1.0
If Imp([0.004, 0.012)) ⇒ Drug (Nicotine)	1	1	1.0	0.047619	1.0
If Imp([-0.021, -0.015)) ⇒ Drug (VSA)	1	1	1.0	0.047619	1.0
If Imp([0.089, 0.097)) ⇒ Drug (Heroin pleiad)	1	1	1.0	0.047619	1.0
If N([*, -0.266)) ⇒ Drug (Caffeine)	1	1	1.0	0.047619	1.0
If TH([-0.911, -0.848)) AND E ([-0.291, -0.237)) ⇒ Drug (Heroin)	1	1	1.0	0.047619	1.0
If TH([-0.680, -0.624)) AND E ([0.024, 0.061)) ⇒ Drug (Ketamine)	1	1	1.0	0.047619	1.0
If TH([-0.448, -0.400)) AND E ([-0.135, -0.126)) ⇒ Drug (Legal highs)	1	1	1.0	0.047619	1.0
If TH([-0.766, -0.680)) AND E ([-0.152, -0.135)) ⇒ Drug (LSD)	1	1	1.0	0.047619	1.0
If Age([-0.509, -0.449)) ⇒ Drug (Methadone)	1	1	1.0	0.047619	1.0
If Age([-0.734, -0.698)) ⇒ Drug (MMushrooms)	1	1	1.0	0.047619	1.0
If Age([-0.581, -0.577)) ⇒ Drug (Nicotine)	1	1	1.0	0.047619	1.0
If Age([*, -0.824)) ⇒ Drug (VSA)	1	1	1.0	0.047619	1.0
If Age([-0.622, -0.593)) ⇒ Drug (Heroin pleiad)	1	1	1.0	0.047619	1.0
If Age([-0.577, -0.572)) ⇒ Drug (Ecstasy pleiad)	1	1	1.0	0.047619	1.0
If Age([-0.449, -0.386)) ⇒ Drug (Benz. pleiad)	1	1	1.0	0.047619	1.0
If O([*, -0.084)) ⇒ Drug (Alcohol)	1	1	1.0	0.047619	1.0
If O([0.346, 0.359)) ⇒ Drug (Amphetamines)	1	1	1.0	0.047619	1.0
If O([-0.084, 0.002)) ⇒ Drug (Amyl nitrite)	1	1	1.0	0.047619	1.0
If O([0.433, 0.444)) ⇒ Drug (Benz.)	1	1	1.0	0.047619	1.0
If O([0.517, 0.548)) ⇒ Drug (Cannabis)	1	1	1.0	0.047619	1.0
If C ([-0.180, -0.174)) ⇒ Drug (Cocaine)	1	1	1.0	0.047619	1.0
If C ([*, -0.428)) ⇒ Drug (Caffeine)	1	1	1.0	0.047619	1.0
If C ([-0.087, -0.066)) ⇒ Drug (Crack)	1	1	1.0	0.047619	1.0
If C ([-0.174, -0.171)) ⇒ Drug (Ecstasy)	1	1	1.0	0.047619	1.0
If C ([0.004, 0.027)) ⇒ Drug (Heroin)	1	1	1.0	0.047619	1.0
If C ([-0.191, -0.187)) ⇒ Drug (Ketamine)	1	1	1.0	0.047619	1.0
If SS([0.477, 0.494)) ⇒ Drug (Legal highs)	1	1	1.0	0.047619	1.0
If SS([0.298, 0.309)) ⇒ Drug (LSD)	1	1	1.0	0.047619	1.0
If SS([0.181, 0.291)) ⇒ Drug (Methadone)	1	1	1.0	0.047619	1.0
If SS([0.291, 0.298)) ⇒ Drug (MMushrooms)	1	1	1.0	0.047619	1.0
If SS([0.463, 0.477)) ⇒ Drug (Nicotine)	1	1	1.0	0.047619	1.0
If SS([0.309, 0.335)) ⇒ Drug (VSA)	1	1	1.0	0.047619	1.0
If A([-0.068, -0.060)) ⇒ Drug (Caffeine)	1	1	1.0	0.047619	1.0
If A([-0.060, -0.057)) ⇒ Drug (Crack)	1	1	1.0	0.047619	1.0
If A([-0.028, -0.022)) ⇒ Drug (Ecstasy)	1	1	1.0	0.047619	1.0
If A([*, -0.271)) ⇒ Drug (Heroin)	1	1	1.0	0.047619	1.0
If A([-0.076, -0.068)) ⇒ Drug (Ketamine)	1	1	1.0	0.047619	1.0
If A([-0.057, -0.043)) ⇒ Drug (Legal highs)	1	1	1.0	0.047619	1.0
If A([-0.008, 0.033)) ⇒ Drug (LSD)	1	1	1.0	0.047619	1.0
If A([-0.271, -0.258)) ⇒ Drug (Heroin pleiad)	1	1	1.0	0.047619	1.0
If A([-0.090, -0.076)) ⇒ Drug (Ecstasy pleiad)	1	1	1.0	0.047619	1.0
If A([-0.226, -0.197)) ⇒ Drug (Benz. pleiad)	1	1	1.0	0.047619	1.0
If Edu([0.236, *)) ⇒ Drug (Alcohol)	1	1	1.0	0.047619	1.0
If Edu([-0.256, -0.233)) ⇒ Drug (Amphetamines)	1	1	1.0	0.047619	1.0
If Edu([0.059, 0.107)) ⇒ Drug (Amyl nitrite)	1	1	1.0	0.047619	1.0
If Edu([-0.214, -0.204)) ⇒ Drug (Legal highs)	1	1	1.0	0.047619	1.0
If Edu([-0.148, -0.119)) ⇒ Drug (LSD)	1	1	1.0	0.047619	1.0
If Edu([-0.365, -0.316)) ⇒ Drug (Methadone)	1	1	1.0	0.047619	1.0
If Edu([-0.204, -0.193)) ⇒ Drug (MMushrooms)	1	1	1.0	0.047619	1.0
If TH([-0.510, -0.479)) AND E ([0.139, 0.323)) ⇒ Drug (Cocaine)	1	1	1.0	0.047619	1.0
If TH([0.374, *)) AND E ([0.323, *)) ⇒ Drug (Caffeine)	1	1	1.0	0.047619	1.0
If TH([*, -0.911)) AND E ([-0.045, -0.006)) ⇒ Drug (Crack)	1	1	1.0	0.047619	1.0
If TH([-0.479, -0.448)) AND E ([0.087, 0.100)) ⇒ Drug (Ecstasy)	1	1	1.0	0.047619	1.0
If TH([-0.848, -0.766)) AND E ([-0.006, 0.024)) ⇒ Drug (VSA)	1	1	1.0	0.047619	1.0
If TH([-0.400, -0.332)) AND E ([-0.099, -0.082)) ⇒ Drug (Heroin pleiad)	1	1	1.0	0.047619	1.0
If TH([0.224, 0.374)) AND E ([-0.237, -0.206)) ⇒ Drug (Ecstasy pleiad)	1	1	1.0	0.047619	1.0
If TH([-0.182, 0.031)) AND E ([-0.126, -0.114)) ⇒ Drug (Benz. pleiad)	1	1	1.0	0.047619	1.0

Table 5: Drug groups according to the values which differ from the sample mean for groups of users for the year-based user/non-user.

Group No.		N	E	O	A	C
1	Alcohol, Chocolate, Caffeine multicolumn5cNeutral value Neutral value Neutral value Neutral value Neutral value					
2	Nicotine	high	Neutral	high	Neutral	low
3	Amphetamines, Amyl nitrite,Cannabis, Cocaine, Crack, Legal highs, and VSA	high	Neutral	high	low	low
4	Benzodiazepines, Heroin, and Methadone	high	low	high	low	low
5	LSD	Neutral	Neutral	high	Neutral	low
6	Ecstasy	Neutral	high	high	low	low
7	Magic Mushrooms	Neutral	Neutral	high	low	low
8	Ketamine	high	high	high	low	low

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