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Original Article

Human Addictive Behavior Classification (ABC) using Adaptive Quantum Mean Value Approach

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Abstract - *Making decisions with uncertainty contextually, such as human cognitive behaviors such as addictions, emotions, and skills has complex systems to understand. To analyze the addiction behavior context, there is a need for a cognitive psychometric-based decision-making classification approach as well as symptom validation tests for uncertain addiction circumstances. In Kolmogorov, probability theory (KPT) is used for low and less symptom validation, and Quantum probability theory (QPT) approaches are used for highly addiction-based symptom validation. But, most occasional triers have never been understood whether they are in addiction or not unless they have been affected by addiction behavior syndrome. The occasional context becomes an uncertain activity. Decision-making in an uncertain context has quite a challenge in analyzing and predicting the human behavior pattern. The majority of human behaviors and conscious routines become unconscious, compulsive activities. Hence the routine behaviors might be turned into addictive behaviors, which are the state of being unable to avoid acts. The main objective is to develop a non-cognitive-based classification model to help people analyze their consciousness of addictive behaviors. In this context, this paper discusses a psychometric cognitive modeling method for forecasting the amount of addiction classification system model using adaptive quantum and mean value (QMV) formulation. Multiple addiction contexts were used to test the efficacy of QMV. The adaptive QMV approach has been effectively supported for noncognitive tests and addiction symptom validation. This proposal is highly intense to make cognitive, conscious-based measures for an uncertain context, addiction prediction, and effective classification. In conclusion, the consistency of human behavior makes a huge difference between addictive and non-addictive.*

Keywords - *Addictive assessment, Behavior classification, Multi-addict context, Noncognitive test, Symptom validation, Quantum mean value.*

1. Introduction

Addiction is a kind of stimulating form of a tendency to execute the repetitive activity. Even though individuals know that certain compulsions are not serving their goals, they nonetheless feel "compelled" to carry them out [1]. Addiction is a "repetitive, or automatic, activity linked to a negative outcome expectation that adds to the sense of being compelled to act despite adverse consequences"[2]. Generally, addiction types of emotional and cognitive dysfunctions are uncertain context execution.

Due to the inconsistency of human behavior traits, still unable to predict, interpret, and decisions making about addiction classification. Decision-making in an uncertain context has quite a challenge in analyzing and predicting the human behavior pattern. The majority of human behaviors and conscious routines become unconscious, compulsive activities.

Hence the routine behavior might be turned into an addictive behavior which is the state of being unable to avoid acts.
Multiple human psychological and cognitive traits include addiction, anger, and stress. Among the different psychopathic issues, we have concentrated on addiction behavior diagnosing using cognitive psychometrics since numerous studies conclude that the significance of human brain cognitive and behavioral traits has not yet been addressed [3].

There is still more research that needs to be done, as well as an investigation into the use of a human psychometric model to quantify lifestyle activities, particularly in addiction behavior classification. An addiction transforms a person's physiological and psychological characteristics. Most cognitive theories agree that cognitive architecture is a data-type-free framework miming the entire human cognitive structure [4-5]. Moreover, consistent-based classification is essential in symptom validity tests, as shown in figure 1.

However, the cognitive assessment test consists of a cognitive test and a noncognitive test, the symptom validation test at noncognitive is highly supported in pretreatment for behavioral traits. Self-diagnosing psychological and physical dependencies such as an addiction-related disorder can be attained through the symptom validation test.

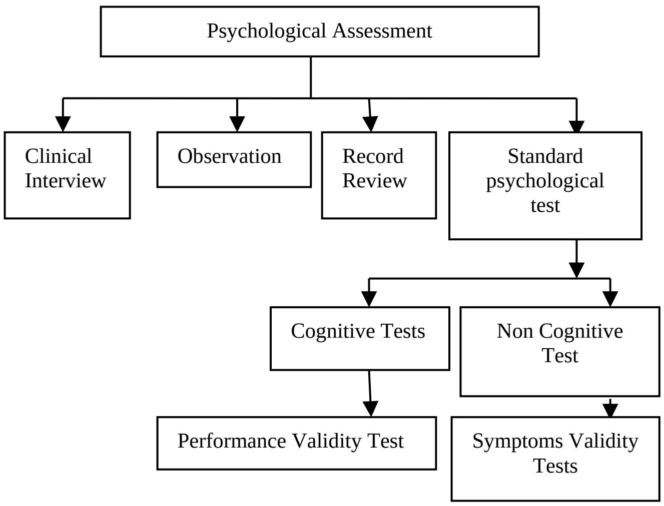

Fig 1. Cognitive Assessment Tests

As a result, this study tends to develop a framework model allowing individuals to input their lifestyle activities and then provide suggestions based on those values under the addiction behavior symptom test. Sometimes human behavior becomes compulsive, sensitive, and time-consuming activities. Monitoring perspectives must be the tracking metric. An addiction is a compulsive behavior that begins as a pleasurable activity and progresses to serious demand and compulsive conduct. The context of an addicted behavior is ambiguous. According to past research, there is no commonly acknowledged addiction contextually metric.

Making a cognition model for self-awareness in an addictive context is essential. Since unconscious, sometimes occasional activity might be unnoticeable but highly impact addictive perception. Structure the addictive classification for different addiction contexts and determining the threshold value for each addict context is quite difficult because the quantity and quality of the measured parameters differ.

The QMV model exploited quantity-based mean values as inputs for this generic self-diagnostic categorization model for optimal remembrance. Moreover, the QMV is adequate as a quantity parameter since it is memorable for self-analyzing quantity in multi contexts. Substance-based addictions (SBA) measure the quantity of consumption-seeking substances. In contrast, virtual (VBA) measures the spending time, and both measure the quantity with the relevant period.

2. Related Study

Decision-making on psychological traits for self-diagnosing is quite a complex task. Addiction is a psychological, physiological dependency mindset over substance and behavioral. There was a need for a self-diagnosing mechanism to treat and recover from these emotional and behavioral dependencies. To evolve psychometrics, cognitive assessment highly supports making more conscious of the addiction activity.

Furthermore, there is still a lack of clarity as to whether or not a person is addicted to certain things. Quantity may be the physical substance, and virtual addictive behavior can be tracked by the amount of quality time spent on such leisure activities [6]. Because cognitive contextuality contains different paradoxes, quantum probability theory (QPT) has proved more effective in context measurement than Kolmogorov probability theory (KPT).KPT and QPT are more suited for low and extreme context decision classification in this declaration. Because QP theory is a formal framework for assigning probabilities to occurrences, some normative arguments for QP theory, similar to those for classical probability (CP) theory, can be developed. Furthermore, QP processes appear to have natural interpretations regarding well-known heuristics, such as representativeness and availability [7-8]. As a result, the threshold or mean value-based classification is not determined or trailing.

Dynamic threshold value has been essential in cognitive psychometric development in these considerations. The mean value theorem migrates a quantum mechanism for a different mid-value in the context of input values [9]. Furthermore, the Quantum mechanism outperforms the fuzzy set regarding multi-addictive contextuality. Quantum decision theory was established utilizing mathematical Hilbert spaces to aid in the measurement of uncertainty [10] substantially.

Another name for the quarter law is that it is concerned with quantitative predictions on the subjectivity of people's decisions. For model-based RL, there are numerous ways to capture model uncertainty. Uncertainty is directly included in Gaussian processes and Bayesian neural networks; however, they are not ideal for complex tasks. Model ensembles and Dropout are two further methods for approximating model uncertainty. In the presence of uncertainties, the inverse analysis also includes identifying uncertainty and validating the model's applicability simultaneously. In the context of this, inverse analysis has been applied to the topic of fuzzy arithmetic, resulting in inverse fuzzy arithmetic depending on the technique of change [11].

2.1. Cognitive Psychometric Model

Furthermore, numerous studies were carried out for cognitive psychometric model development. The standard software framework (SSF), developed by Hamrick, combines many recurrent neural networks to produce higher constructs like cognitive architectures inspired by the human brain. The basic flaw is that it has no real-world applicability [12]. Then Reed presented a modern perceptual adaptive system (MPAS), this model working with the support of dopamine neuromodulation processing devices with cortical outcomes [13]. Beyond formal testing, there is still uncertainty regarding its application in real life. After that, the neural adaptive mind control cognitive framework (AMCCF) by wood and the team was implemented at HumMod simulation framework, providing basic and limited level psychological diagnosing [14]. After that, Di Nuovo & McClelland developed cognitive structure-based software but did not support complex tasks [15]. Then dual process thought, and rationality theories are based on the cognitive model proposed by Danese [16]. This system is implemented in convergent and divergent systems.

Most recently, Zhang and her team proposed a deep learning-assisted integrated prediction model (DLIPM) [3]. This model has achieved significant implementations in cognitive assessment at performance validation tests. They have tried noncognitive measures using AI-based prediction of child mental health issues. Furthermore, existing AI approaches do not fully account for the complexity and unique aspects of the brain, necessitating new approaches to the cognitive modeling dilemma [17].In addition to traditional parameter identification approaches, the uncertainty of model parameters can be assessed using fuzzy numbers. In contrast to this broad approach, additional notions have more limited use. These ideas share the requirement for a unique character in the relationships between fuzzy-valued quantities and the restriction to specific forms of membership functions.

3. Proposed Methodology

As per our studies, the Quantum and Mean value (QMV) theorem provides the best threshold value of distinct contextuality.QMV is an actual context-based adaptation formula based on individual, uncertain, and unique values which lead to actual outcomes. Based on QMV values, self-evaluation can be carried out on the user, providing the idea of an addiction's relapse risk rate. The QMV values represent the mean of the threshold. Compared to fuzzy sets and other reinforcement machine learning algorithms, QMV works much better in cognitive psychometric modeling. To examine the addicted human cognitive psychometric modeling, decision-making on rational addiction classification depending on the strength is effective. It is critical to examine the addiction disorder from a variety of angles. Since this consumption or action sense environment is dynamic, it is difficult to assess the multi-viewpoint of addictions, trigger variables, and repercussions.

Furthermore, determining the human psychometric addictive pattern necessitates thoroughly examining drug and behavior-based addiction. From a broad standpoint, every addiction environment differs only slightly. The implications differ considerably on the addiction and the initial stimulus, with detrimental impacts on physical and mental health. In this regard, examining the interaction between substance and virtual-based addiction has helped researchers better understand the psychometric pattern of cognitive addictive behavior. These analysis patterns reveal intriguing insights into the interrelationships between substance and virtual-based addictions. According to social identity theory, individuals can define themselves depending on their behavior by comparing themselves to other social groupings. Similarly, this pattern assists people in evaluating whether or not they are addicted and, if so, what the long-term effects may be.

The above context of addiction is more interconnected to the compulsiveness used and excessive time spent. The impacts and consequences, on the other hand, are highly contradictory. In both circumstances, characterization of the addictive environment necessitates using psychometric factors to determine the amount of addictiveness. Because the irregularity of repeating activities may impact addictive classification, in an addictive SBA, the quantity consumption metric can classify addiction levels as extremely addictive, moderately addictive, or non-addictive because the frequency of substance seeking is variable. According to the theory of planned behavior, beliefs determine attitudes hypothesized that detrimental beliefs would be correlated to perceived risk. The frequency of substance consumption can be classified based on the addictive context.

In multi-addiction contexts, the acts are unique and recurring. Longevity and consistency are important factors in determining the median of any situation or action. Using the Quantum mean value, determine whether the addictive environment is intense, occasional repeater, or low addictive. The input could be a quantity parameter, a substance consumption value, or a quality parameter, such as spending time with gadgets for virtual systems and calculating the average with total spending time from the start point.

This Quantum Mean value pinpoints the precise location of the individual. This technique is broad and effectively delivers addictive analysis.SBA and VBA can be quantified using a quantity parameter in an addictive context.

3.1. QMV-based threshold value setting for addictive context

For the stereotype of thinking, consistency of attitude behaviors is critical. For consistent contextuality measurement, a psychometric measure is required. Much research shows that there is a lack of uniform contextuality measurement. Because access to an addictive context is intermittent, the consistency of the addictive context varies dynamically. High or low addictive contexts can be classified based on dynamic QMV context values. Some addictive situations may be form-dependent, such as regular access activity and other irregular access.

The extent of dependence on routine attitude behavior varies from person to person. As a result, constant access may vary due to compulsive-dependent tendencies. Personal characteristics of individuals may have a definite place on a continuum of diverse personality traits, according to Allport's Theory of Personality [18].

3.1.1. Quantification Calculus for classification

For example, if X has been performing the same acts 8 times per day for the past year, he may be able to quit; however, if Y has been performing the same acts 3 times per day for the past 8 years, his chances of quitting are slim. For example, If X has been playing an online game for 8 hours per day for the past year, it is conceivable to quit; if Y has been playing an online game for 8 years, the cessation rate is low, as shown in fig 2.

Average Qsba= (Sum of In taking on one day*Total in taking in recent period/per day)
Qsba= (Avg Qsba*Total Quantity Consumption period/per days)
(Qsba-Quantity of substance based addiction)

Fig. 2 Average finding Substance based on addiction

Whenever the QMV is high, the risk of relapse is also high, and vice versa. Because the durability and consistency of repeating acts have an impact on and render highly trustworthy, reliable, and quit chores high risk. The dynamic threshold was estimated using QMV in a multi-addictive scenario. The P value represents the average quantity consumed or time spent on virtual platforms. The p-value may differ depending on the context.

The high, low, or moderate addictive grade can be determined by comparing the mean consumption and the length of time spent in an addictive context, as shown in fig 2. The classical rational decision-making model argues that decision-makers characterize an issue in detail, comprehend all viable alternatives and their ramifications, and choose the optimal course of action after weighing all available possibilities.

3.1.2. Adaptive Quantum Probability for dynamic ABC

Let us assume that x has played virtual games on smartphones for only 2 hours/per month for the past 8 years. Similarly, another Z has played 8 hours/per day for only recent 2 years, but he is interested in quitting. In this context, we might think Y is highly likely to be an addictive person than X since X spent time with online games only 2 hours/per month, but Z played 6 hours/per day. For an addictive context with one more possible, unnoticeable, or less consideration, the probability is vital for predicting the addictive context. The consistency context means how long the habits are explored rather than quantity.

3.2. Uncertain Contextual contradictions

Let us assume that persons A, B, and C are addicted. They all have similar online gaming addictions considered as base DE.But the consistency might vary which can be {b,c,d,e}.Hence the base DE is the same for all, but the consistency is different. As shown in fig 3, pseudocode, triangle ADE, AD-based AB, and AE-based AC are varied based on the variable values. Similarly, based on internal stimulus consistency, the above formula values the outlines or varies and provides different decision classification.

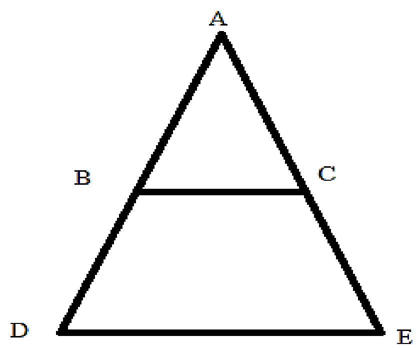

Fig. 3 Dynamic base contexts and pseudocode

Let's consider the $\triangle$ADE, the $\frac{AB}{AD} = \frac{c}{b}$ as an addiction behavior pattern, which might be the same, but the consistency

It might cause a difference. Hence consider ,AC=d, AE=e,

Here the addiction pattern might be, $\frac{AC}{AE} = \frac{d}{e}$

But behavior inconsistency leads, $\frac{AB}{AD} \neq \frac{AC}{AE}$

Hence the consistency fallacy arrives based on dependency values. The occasional triers are highly likely to be addictive much more than heavy users in a considerable amount of time. Since the self-saturation points are varied, which might decrease those who are high volume using or heavy consuming some addictive and repeated activities, but limited users have many cues for seeking high amounts for self-saturation.

Especially in human behavioral analysis, which is solely interrelated with uncertain context. The analysis, observation, and prediction-based conclusions in an uncertain behavioral context are highly contradicted with actual results. It is challenging to structure the addictive classification for distinct addict contexts and to determine the threshold value for each addict situation. Because the quantity and quality of the measured behavioral consumption constantly vary based on contextual circumstances. The consistency-based addiction behavior classification is performed under symptom validation and noncognitive measure.

4. Results and Discussions

Many addictive people have a high intensive cognitive bind of their interest-based addictive activity. The compulsive cognitive period plays a vital role in addiction. Whenever the interval becomes loosely consistent, then the recovery rate from the addictive person is high and vice versa.

4.1. Dataset Collection

Analysis of an addiction behavior required numerous contexts such as substance and virtual-related addiction datasets. The 630 multi-addiction contexts sampling datasets were collected from open datasets from HHS.gov.in. (i) Tobacco and drug consumption datasets (ii) Worldwide virtual addiction datasets.

4.2. Technical and actual outcome contradiction

Psychometric design for addiction classification required multiple forms of addiction contexts: tobacco, drugs, smartphone, virtual platforms, and gambling addiction activities. As previously stated, human addiction behavior is a psychological and physiological tendency-building pattern. So there is a need to analyze the existing data prediction and actual outcomes of both substances such as tobacco, drugs related addiction as well virtual platform addiction such as virtual reality gaming addiction, gambling addiction, and smartphone addiction such as compulsive buying through e-commerce and continuous video watching as shown in table 1.

As per sample, outcome analysis with existing symptom validation test, in 126 datasets of each addiction context, value predicted with an actual difference 25-35 quantity contradiction result. This contradiction difference is solely based on the input of multiple addiction people, self-diagnosing outcomes. It indicates that symptom validation tests need to be designed for the prior treatment of psychological addiction classification.

Table 1. Uncertain contextual contradiction

Addiction-based outcomes contradictions				
Addiction Behavior	Analysis	Observation	**Prediction**	**Actual**
Tobacco based addiction	30	50	40	70
Drugs based addiction	35	60	45	65
Smartphone based addiction	20	40	50	80
Virtual Platform addiction	40	50	55	70
Gambling addiction	30	45	40	75

For example, person Z has played online gaming with 18hrs/per day for the past 2 years, and X has been playing 2 hrs/per day for the past 10 years with irregular intervals such as monthly or yearly. Z has a possible recovery from addiction than X. Since consistency plays a vital role in the addiction behavior formation. A recent study on cognition psychological measures of contextuality with state context property and Kolmogorov probability theory supports zero contextuality and quantum probability theory extreme contextuality. So there is a need for a psychometric for occasional and middle-level addiction diagnosing. The proposed QMV approach provides a middle level. Occasional addiction individuals can rate their addiction level based on their self-analysis and addiction consumption value.

5. Implications of the QMV Approach

Many non-addictive and occasionally addictive people are tightly consistent with addictive activity rather than addictive people. Since the consistency-based associate's addictive behavior highly indulges with the stimulus craving for a certain activity. Person X might occasionally play or consume substances for regular periods that have high potential as an addictive person as a sample model. Hence the recovery rate from a particular addictive behavior has a high risk based on consistency.

There is a necessity for an intermediate threshold value due to the variability of the addictive context so that occasional and regular habituation can occur. Because of the descriptive nature of QPT, a hybrid of quantum and mean value theorems serves as an intersection for many contexts and perspectives. The risk of relapse is also associated with the level of addiction. The Poisson distribution is the most common probabilistic framework for multi-model contexts. Nonetheless, the negative binomial distribution has often been adopted because of the common over-dispersion in addictive data. As previously stated, the relapse risk rate (RRR) is exactly related to QMV, as shown in fig 4. Self-addiction/consumption value and addiction-based effects are represented in the figure.

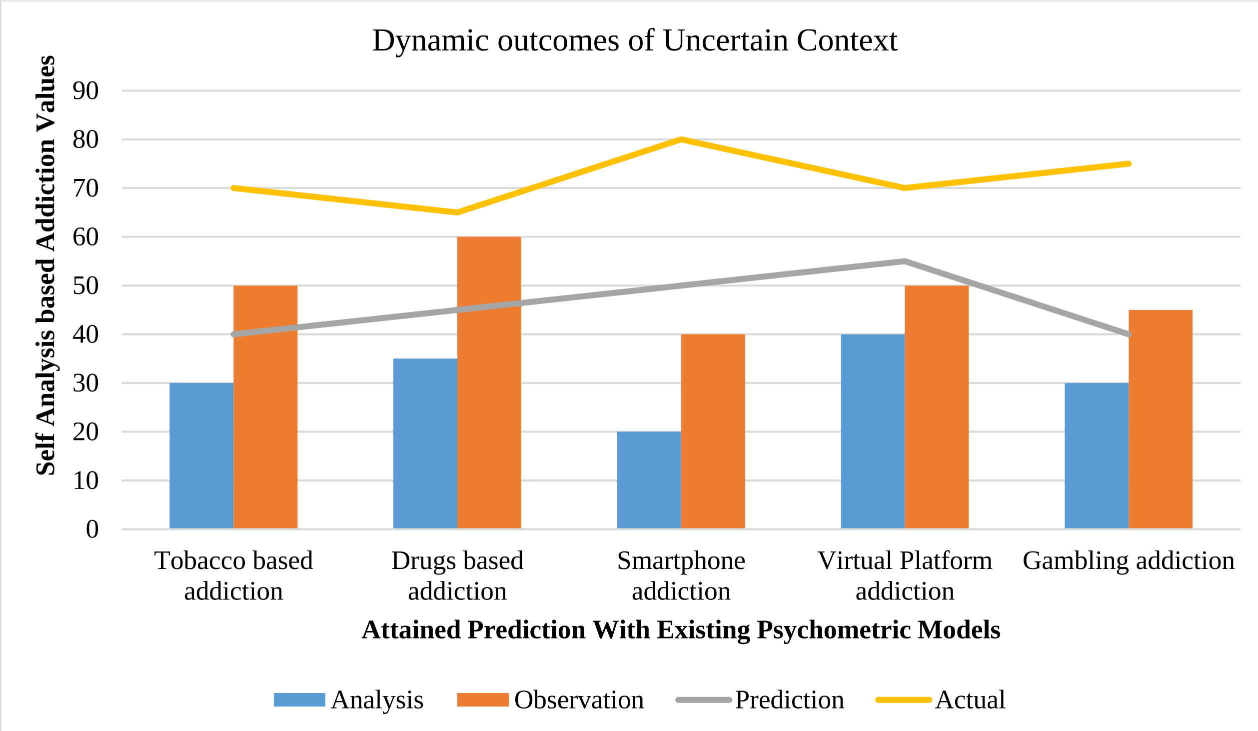

Fig. 4 Technical outcomes and actual (QMV) outcomes

5.1. QMV approach to Multi-Addiction Contexts

This QMV model tested the Q values of 126 samples of five different forms of addiction context in a total of 630 circumstances and determined the Mean Q. For example, tobacco based on cigarette addiction context and the consumption of addiction values observed from samples. As a result of the Q and Mean Q and Y and Mean of Y-based classification factors, addictive grades can be classed as low, moderate, and high. Because the dynamics of context change, judgments are made differently depending on the year and amount of substance context and the year of experience and quantity of spending period analysis provided in virtual-based context.

On the other hand, addiction data is prone to heterogeneity because it is typically acquired from various addictive situations. The fixed effects negative binomial model, which accounts for variety, only considers the average effects of heterogeneity across observations. The mixed effects negative binomial model combines fixed and random effects and is a viable option. Because it accounts for the various effects on different addictive contexts, this mixed effects model delivers more realistic estimates.

The virtual-based addictive setting was linked to psychological and emotional diseases rather than physical health issues. Virtual addictive situations include frequently monitoring social media, spending excessive time playing online games, focusing too much on internet snuffing, and so on. Because of these VBA circumstances, loneliness is favorably associated with internet-based contact with others, avoiding interpersonal communication, and lack of self-understanding is positively associated with limited time spent on the objective in their individual lives. Gaming Platform applications encourage players to use incentive offers as a stimulant regularly. These factors contribute to compulsive mental and psychological behaviors.

Conversely, virtual-based addictive contexts have a greater direct impact on cognitive biases than physical health difficulties. Cognitive errors are sometimes referred to as cognitive failures. To correct cognitive errors things that a person should be competent [19]. Cognitive failures such as poor memory, distractibility, and blunders result from cognitive failures. As a result of a lapse in cognitive processing, these forms of cognitive failures directly impact mental health. Complexity theory is an ideal tool for accommodating a social event's deterministic and changing components [20].

5.1.1. QMV approach to Self-Awareness

However, these numerical contexts merely lie on addiction-forming behavior, stimulating the tendency in the same way virtual miniature causes compulsive seeking. According to Dienes and Perner, the brain processes information through rule-based explicit and skill-based implicit systems [21].

The QMV model analyzed multiple addiction contexts: tobacco, drugs, smartphone, virtual platforms, and gambling addiction activities. QMV-based conclusions have effectively classified the decision about the addiction with analysis, observation, and prediction model, as shown in fig 5.

Self-addiction/consumption value and effective cognitive and noncognitive tests are represented in the figure. Supervised and unsupervised learning algorithms are similar to rule and skill-based cognitive processes. Since supervised and unsupervised learning is activities with and without labeling, they are the same.QPT with fuzzy model and reinforcement machine learning algorithms in comparisons. Longevity and consistency are important factors in determining any situation or action [22]. Using the Quantum mean value, determine whether the addictive environment is intense, occasional repeater, or low addictive.

The input could be a quantity parameter, a substance consumption value, or a quality parameter, such as spending time with gadgets for virtual systems and calculating the average with total spending time from the start point. This Quantum Mean value pinpoints the precise, conscious position of the individual.

5.1.2. QMV significance of an Addiction Behavior

This technique is broad and effectively delivers addictive analysis. Although the activity may be substance or virtual-based addiction, determining an individual's addiction grades for various activities is difficult due to (QMV) based categorization parameters being derived for further classification of addiction grades as high, low, or moderate.

The relapse risk rate can be determined based on the addiction grade, and these RRR values can be used to aid psychometric measurement. Dynamic factors [23]. Consistency, longevity, and consistency diverge significantly, resulting in calamity. So, in the substance and virtual contexts, the quantum mean value

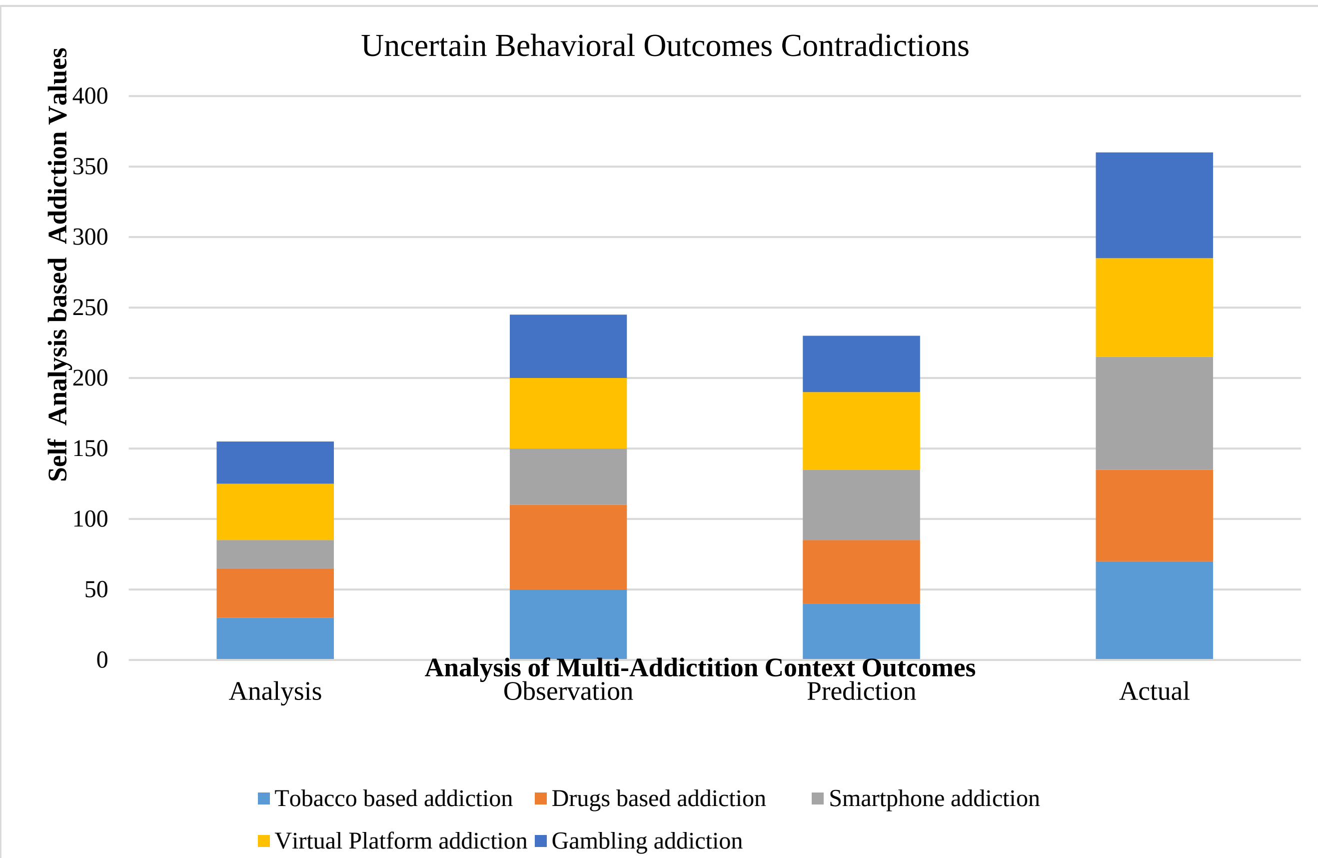

Fig. 5 Actual (QMV) effects over multi-addiction classification

The psychometric measure is a comparison model with KPT, QPT, and QMVT, as shown in fig.6. Self-addiction/consumption value and effective performances of noncognitive tests are represented in the figure. KPT is effective in low-addictive situations, such as those with a low amount of use and a short period of addiction. QPT is best suited to extreme cases involving high intake levels in an addictive environment. QMVT has high accuracy, consistency, duration, and relapse risk rate for addictive parameters.

Numerous psychological dependencies and emotional traits lead to dysfunction of cognitive processing and depression states [24-25]. So it is essential to develop modern, cognitive, and effective psychometric methods for pretreatment, such as addiction behavior classification

5.2. Limitations and implications

As previously stated, our primary goal is to derive this psychometric addicted self-diagnosing model in multi-addiction contexts by applying a quantity parameter to measure it. In evaluation metrics, QMV analysis has been taken three important concerns for determining the efficacy of the self-diagnosing addictive psychometric model.

These metrics are compared with the QMV model with reinforcement and fuzzy set-based classification systems. The Fuzzyset model was effective with the more accurate inputs and less dataset.

A very limited sampling test with multi-context data consists of a substance with a measurable quantity and a virtual context where time is spent as measured. This QMV-based classification model aids in estimating approximate mean values and predicting individual decision-making on addictive grades. The outcomes of this study can significantly make awareness of relapse from addiction. When the QMV score is high, there is a greater risk of relapsing or quitting the addiction, which can be treated with suitable medical treatment and psychological counseling, depending on the results.

Moreover, the occasional and uncertain addiction context for prior treatment before reaching the serious negative outcomes, then cognitive, symptom validation test essential for self-awareness of individual addiction states. This QMV approach might construct a noncognitive structure assessment but is mainly developed for individuals self-diagnosing their addiction grade, which is supported to attain self-awareness of addiction behavior.

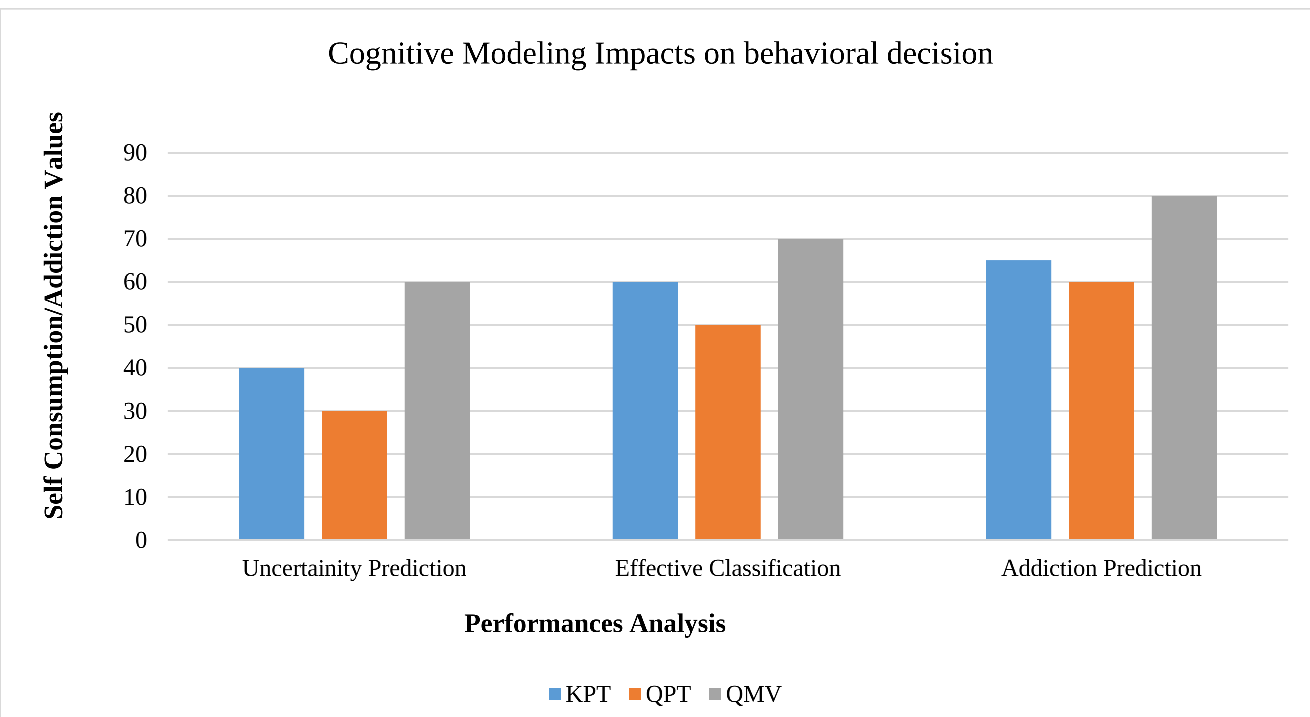

Fig. 6 Effectiveness of QMV

6. Conclusion and Future Works

Addiction is a cognitive-based habitual trait that leads to positive and negative outcomes based on intensive action characteristics. Addiction is not only related to physical object dependence or substance addiction. It is also a behavioral addiction such as compulsive buying through e-commerce and online gaming addiction. These addictions make the user into application dependent on virtual addiction. Given the ambiguous nature of addiction, making decisions about addictive behavior necessitates self-awareness. Self-awareness is becoming increasingly important. Because self-awareness can provide psychological protection against addiction behaviors in the long run. In this connection, there is essentially the cognitive self-diagnostic model to increase awareness of addictive behavior [26].

In this regard, the QMV model is designed as a psychometric cognitive modeling method based on the QMV formulation for forecasting the addiction behavior classification in symptom validation. Multiple addiction contexts were applied to test the efficacy of QMV, fuzzy set, and reinforcement algorithms. This multi-context model, an addictive context is quantified using a quantity parameter. Based on this, we have developed the Quantum Mean Value (QMV) formulation, which allows us to compare average inputs and assess if a person is addicted to a high, low, or moderate level of addictiveness. Furthermore, based on QMV, it is possible to anticipate the addictive quit (Relapse risk rate) and treatment options for physical and psychological health.

However, the QMV cognitive model efficiently measures the consistency point in a multi-addictive environment, allowing for precise measurement and classification of the addictive grade. Compared to non-consistency people, the consistency oriented perspective gives the occasional triers a higher possibility for psychological addiction. A relapse risk rate can also be determined. RRR values could be used to recommend medical and psychological treatment. Anyone can use RRR to calculate themselves for any addictive activity, which is extremely supportive in controlling the addictive activity. The adaptive QMV model has the potential and works by the individual, self-consistency, and conscious input based on addiction behavior classification. The neurocognitive system plays a vital role in human behavior classification. Our next goal is to turn these cognitive models into a real-time application leveraging multi-computing fusion technology.

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