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# Human Behavior Analysis Using Machine Learning

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**Abstract.** *The study and analysis of human behavior have been longstanding challenges in various fields such as psychology, sociology, and anthropology. With the advent of advanced technologies and the proliferation of data, machine learning has emerged as a powerful tool for deciphering and understanding complex human behaviors. This research aims to explore the application of machine learning techniques in the analysis of human behavior, leveraging diverse datasets and cutting-edge algorithms to gain insights into individual and collective actions. The research methodology involves the collection of multidimensional data sources, including but not limited to social media interactions, physiological measurements, and environmental factors. These datasets are preprocessed and integrated to create a comprehensive representation of human behavior. Machine learning models, ranging from traditional statistical methods to deep learning architectures, are then applied to uncover patterns, correlations, and predictive insights from the data. Machine learning algorithms can analyze patterns in behavior to identify potential signs of mental health issues, enabling early intervention and treatment. Tracking behavioral data can help in managing chronic conditions by providing insights into lifestyle choices, adherence to treatment plans, and overall well-being. Machine learning models can identify unusual patterns of behavior, which is crucial for security purposes. This can include recognizing suspicious activities in public spaces or flagging unusual behavior in online environments. The purpose of this study is to explore the challenges of multiple attribute decision-making when dealing with intuitionist fuzzy information. In this scenario, the attribute weights are not entirely known, and the attribute values are represented by intuitionist fuzzy numbers. To determine the attribute weights, an optimization model is constructed based on the traditional grey relational analysis (GRA) fundamental principles. The proposed method involves calculating the grey relation degree between each alternative and the positive-ideal solution and negative-ideal solution. This degree is then used to define a relative relational degree, which enables the ranking of all alternatives simultaneously with respect to both the positive-ideal solution (PIS) and negative-ideal solution (NIS). From the result 22 is ranked at first position and 45 is ranked at fifth position*
***Keywords:*** *Activities of daily living Behavior, Monitoring Performance, Evaluation Machine Learning, Smart home*

## 1. INTRODUCTION

Advanced machine learning techniques integrated into cognitive computing systems contribute to comprehensive human behavior analysis. These systems employ deep neural networks, natural language processing, and pattern recognition to discern intricate patterns in human behavior. By analyzing diverse data sources, including text, speech, and visual inputs, cognitive computing models can derive meaningful insights into emotions, preferences, and decision-making processes. This multifaceted approach enables a deeper understanding of human behavior, fostering applications in personalized services, mental health monitoring, and adaptive technologies. The synergy of advanced machine learning and cognitive computing empowers systems to interpret and respond to human actions with heightened accuracy and contextual awareness [1] Machine learning methods, ranging from traditional algorithms to deep learning architectures, are scrutinized for their efficacy in deciphering user actions across diverse domains. Current models delve into understanding online behaviors, product preferences, and interaction patterns. Applications span personalized marketing, recommendation systems, and cyber security, showcasing the versatility of these models. The survey provides a comprehensive overview of the evolving landscape, shedding light on the strengths, limitations, and future prospects of machine learning-driven user behavior analysis, offering valuable insights for researchers, practitioners, and industries leveraging these advancements [2] A survey on human computing and machine understanding of human behavior explores the intersection of artificial intelligence and behavioral science. It delves into how machines interpret human actions, emotions, and intentions. This interdisciplinary field investigates applications in human-computer interaction, emotion recognition, and adaptive systems, aiming to enhance technology's ability to comprehend and respond to human behaviors. [3] Detecting P2P (peer-to-peer) botnets involves leveraging network behavior analysis and machine learning. By scrutinizing communication patterns, traffic anomalies, and behavioral deviations within a network, machine learning algorithms can discern the presence of P2P botnet activities. This proactive approach enhances cyber security by swiftly identifying and mitigating the threats posed by peer-to-peer botnets through advanced analysis and pattern recognition techniques. [4]

In cloud computing architectures, user behavior analysis employs machine learning techniques to enhance security and optimize resource allocation. By scrutinizing user interactions and data patterns, machine learning algorithms detect anomalies, potential threats, and usage patterns. This aids in refining access controls, improving system efficiency, and fortifying overall cyber security measures within the dynamic and scalable environment of cloud computing. [5] Open-source facial behavior analysis toolkit that facilitates comprehensive facial expression recognition and tracking. Developed by the Computer Vision Laboratory at the University of Cambridge, Open Face utilizes deep neural networks to detect facial landmarks, expressions, and head poses. Its modular design and accessibility contribute to advancements in emotion analysis, human-computer interaction, and behavioral research. [6] Value-directed human behavior analysis from video involves utilizing partially observable Markov decision processes (POMDPs). This approach integrates decision-making models with video data to infer and understand the underlying values guiding human actions. By considering uncertainties in observations, POMDPs enhance the accuracy of behavioral analysis, enabling applications in fields such as surveillance, robotics, and human-computer interaction. [7] Class-Specific Reference Discriminate Analysis (CSRDA) is a method employed in human behavior analysis that focuses on discriminative feature extraction. Unlike traditional approaches, CSRDA tailors the feature space by incorporating class-specific reference information. This enhances the model's ability to discriminate between different human behaviors, improving accuracy and robustness. CSRDA finds applications in various fields, including surveillance and human-computer interaction, where precise behavior classification is crucial. By refining the feature representation based on class-specific references, this technique contributes to more effective and context-aware human behavior analysis systems, offering valuable insights for applications such as security monitoring and anomaly detection. [8] Daily life behavior monitoring for health assessment, facilitated by machine learning, serves as a bridge between disparate domains. By analyzing routine activities and patterns, machine learning algorithms discern health-related insights. This interdisciplinary approach integrates healthcare and technology, fostering proactive health monitoring and personalized interventions, ultimately bridging the gap between traditional healthcare practices and emerging technological advancements. [9] Open challenges persist in the modeling, analysis, and synthesis of human behavior within human–human and human–machine interactions. Tackling complexities such as context-awareness, real-time adaptation, and ethical considerations remains a priority. Integrating interdisciplinary approaches, addressing data privacy concerns, and refining models for diverse cultural contexts are ongoing focal points to advance the understanding and application of human behavior in interactive systems. [10] Online learning behavior analysis, driven by machine learning, involves studying patterns within digital learning environments. Algorithms examine user interactions, engagement levels, and performance metrics to discern insights. This approach enables personalized learning experiences, early intervention for struggling learners, and the optimization of online education platforms through data-driven decision-making, fostering improved educational outcomes. [11]

A comprehensive review of machine learning and deep learning applications underscores their impact across diverse domains. From natural language processing and computer vision to healthcare and finance, these techniques have revolutionized decision-making processes. Machine learning algorithms, ranging from traditional models to intricate deep neural networks, continue to drive innovation by extracting valuable insights from vast datasets. Their versatility and scalability make them integral in solving complex problems, shaping the future of technology and influencing various industries. [12] Recognizing human actions through shape-motion prototype trees involves a novel approach where algorithms learn and match hierarchical structures representing shape and motion prototypes. This method enhances action recognition by capturing the nuanced relationships between body configurations and movements. The hierarchical tree structure enables effective modeling of complex action sequences, improving accuracy in discerning diverse human activities. By combining shape and motion information in a structured manner, this approach contributes to more robust and nuanced human action recognition systems with broader applications in fields such as surveillance and human-computer interaction. [13].

## 2. MATERIALS AND METHODOLOGY

***2.1. Alternative parameters:*** Age [28, 35, 22, 45, 30]
***2.2. Evaluation parameters:*** Income, Physical Activity (hours/week), Stress Level (1-10), Negative Interactions.

***2.3. Income:*** "Income" refers to the money or financial gains that an individual, household, or business receives regularly, typically in the form of wages, salaries, profits, or other sources. It is a measure of the earnings or revenue generated by an entity over a specific period, often expressed as a gross or net amount after deductions. Income is a crucial economic indicator and plays a central role in determining an individual's or a family's financial well-being and standard of living. Different forms of income include earned income from employment, passive income from investments, and business income from entrepreneurial activities.

***2.4. Physical Activity (hours/week):*** "Physical Activity (hours/week)" refers to the amount of time an individual spends engaging in physical activities over the course of a week. It is a measure used to quantify the level of physical exercise or movement someone incorporates into their routine. This metric is commonly expressed in hours per week and encompasses various activities such as walking, jogging, cycling, swimming, sports, or any form of exercise that contributes to overall physical well-being. Monitoring physical activity is important for assessing and promoting a healthy lifestyle, as regular exercise is associated with numerous health benefits, including cardiovascular fitness, weight management, and mental well-being.

***2.5. Stress Level (1-10):*** "Stress Level (1-10)" refers to a numerical scale used to quantify an individual's perceived level of stress. It is a subjective self-assessment where individuals rate their stress levels on a scale from 1 to 10, with 1 indicating minimal or no stress and 10 representing extremely high stress. This measure is commonly used in surveys, questionnaires, or personal assessments to gauge and communicate the intensity of stress experienced by an individual. It provides a quick and convenient way for individuals to express their stress levels, helping healthcare professionals, researchers, or individuals themselves to better understand and address stress-related concerns.

***2.6. Negative Interactions:*** "Negative Interactions" refer to social or interpersonal exchanges characterized by hostility, conflict, disagreement, or other unfavorable aspects. In various contexts, negative interactions can occur in personal relationships, workplace environments, social settings, or online interactions. These interactions may involve arguments, criticism, rudeness, or any behavior that creates a sense of discomfort, tension, or dissatisfaction among individuals involved. Analyzing negative interactions can be important in fields such as psychology, sociology, or communication studies to understand the impact of unfavorable social exchanges on individuals' well-being, relationships, and overall social dynamics.

***2.7. Method:*** The approach of the "grey system concept" is effective for systematically evaluating systems that involve imprecise information. According to the principles of this concept, information that is openly available is categorized as part of a "white system," while any uncertain or ambiguous knowledge falls under a "black system" [14]. In adherence to this theory, a "grey system" contains the least amount of distinguishable details. Within the framework of the grey systems approach, essential components include Grey Relational Analysis (GRA), grey programming, grey control, and grey decision making. Notably, GRA plays a crucial role in addressing problems that entail intricate interactions among various factors [15]. Consequently, GRA is extensively employed to tackle uncertainty arising from incomplete or fragmented data, making it one of the most frequently utilized techniques for exploring correlations between discrete data sets and making inferences in the context of multiple variables. The primary advantages of Geographic Information Retrieval (GRA) include its computational simplicity, reliance on raw data, and support for sound corporate decision-making [16]. The "Deng's (1982) grey systems approach," widely applied across various domains, has proven successful in handling "imprecise, limited, and unclear information." A specific subset of the grey systems technique, known as Grey Relational Analysis (GRA), is specifically utilized to address issues characterized by intricate interactions among different elements [17].Grey Relational Analysis (GRA) has effectively addressed numerous Multiple Attribute Decision Making (MADM) challenges in various contexts. Examples include employee selection (Olson & Wu, 2006), power distribution system restoration planning (Chen, 2005), integrated circuit marking process examination (Jiang, Tasi, & Wang, 2002), quality function deployment model development (Wu, 2002), and defect detection in silicon wafer slicing (Lin et al., 2006) [18]. GRA simplifies MADM problems by consolidating all similarity measurements for each option into a unified value, thereby transforming the original complex problem into a single-characteristic judgment problem. This approach facilitates the straightforward analysis of diverse solutions with distinct features [19].In the initial phase of GRA, known as the "grey relational generating" phase, the performance of each option is converted, producing a comparison sequence. These sequences form the basis for establishing a "standard sequence (ideal target sequence)." Subsequently, the "grey relational correlation between all similarity variants and the benchmark pattern" is computed [20]. The "grey relational grade" between each comparative and benchmark pattern is then calculated using the obtained "grey relational coefficients." The most advantageous option among all converted equivalent sequences is determined as the one exhibiting "the highest grey relational grade when compared to the reference sequence itself" [21].

## 3. RESULT AND DISCUSSION

**TABLE 1**. Human behavior analysis using machine learning

| AGE | Income | Physical Activity (hours/week) | Stress Level (1-10) | Negative Interactions |
|---|---|---|---|---|
| 28.00 | 50000.00 | 5.00 | 3.00 | 5.00 |
| 35.00 | 750000.00 | 3.00 | 7.00 | 8.00 |
| 22.00 | 30000.00 | 8.00 | 4.00 | 3.00 |
| 45.00 | 90000.00 | 2.00 | 6.00 | 6.00 |
| 30.00 | 60000.00 | 4.00 | 5.00 | 4.00 |

Table 1 shows compare above values Age: The individuals in the sample range from 22 to 45 years old, reflecting a diverse age group. Income: The income levels vary widely, with the lowest income at 30,000 and the highest at 750,000. This suggests a considerable income disparity within the sample. Physical Activity (hours/week): Physical activity levels vary, with individuals engaging in activities ranging from 2 to 8 hours per week. Stress Level (1-10): Stress levels also differ, with scores ranging from 2 to 7. The individuals generally report moderate stress levels. Negative Interactions: Scores for negative interactions range from 3 to 8, indicating variability in reported negative social exchanges. By comparing these factors, one might observe potential correlations or trends within the data, such as whether higher income levels correlate with lower stress or if age influences physical activity. Further statistical analysis or machine learning techniques could provide more insights into the relationships between these variables.

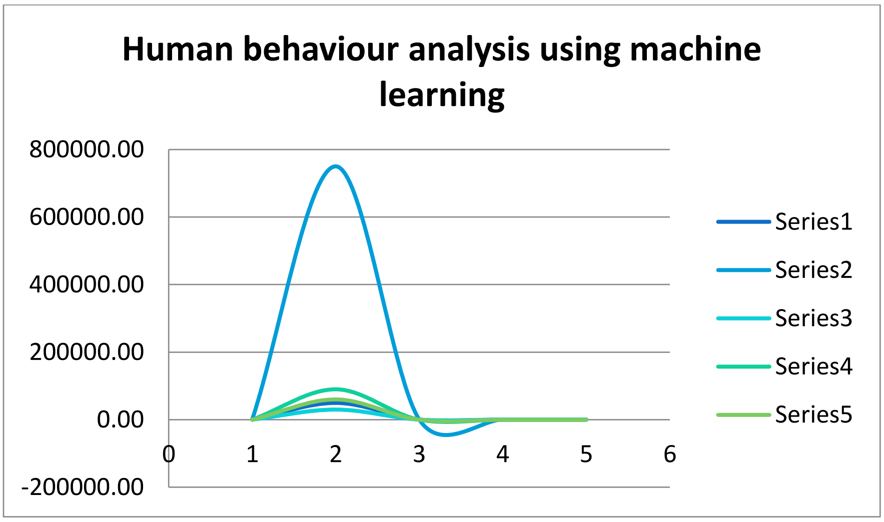


**FIGURE 1.** Human behavior analysis using machine learning

Figure 1 illustrate the graphical representation of Human behavior analysis using machine learning

**TABLE 2**. Normalized data

| Normalized Data | | | |
|---|---|---|---|
| Income | Physical Activity (hours/week) | Stress Level (1-10) | Negative Interactions |
| 0.0278 | 0.5000 | 1.0000 | 0.6000 |
| 1.0000 | 0.1667 | 0.0000 | 0.0000 |
| 0.0000 | 1.0000 | 0.7500 | 1.0000 |
| 0.0833 | 0.0000 | 0.2500 | 0.4000 |
| 0.0417 | 0.3333 | 0.5000 | 0.8000 |

 

In the table 2 shows the variation values of Income, Physical Activity (hours/week), Stress Level (1-10), Negative Interactions. Human behavior analysis using machine learning.

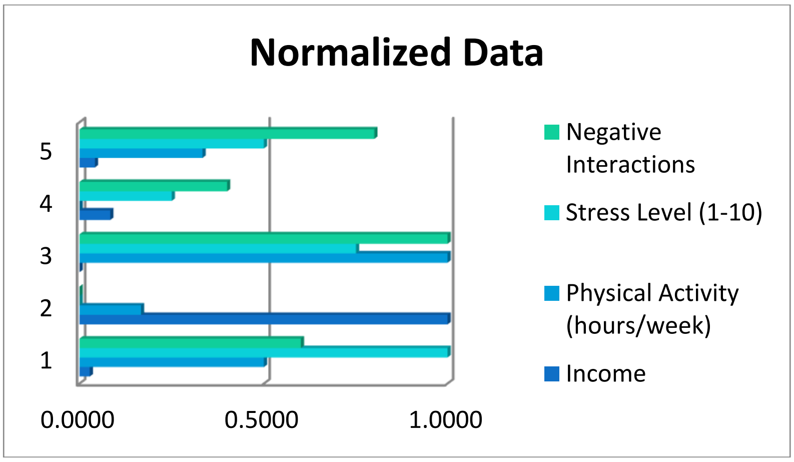


**FIGURE 2.** Normalized data

Figure 2 shows explain normalized data Income: The normalized income values range from 0.0278 to 1.0000, representing a proportion of the original income values. The highest income in the dataset is set to 1.0000, and other values are scaled accordingly. Physical Activity (hours/week): The normalized values for physical activity range from 0.0000 to 1.0000, indicating the proportion of hours spent on physical activity relative to the maximum observed value. Stress Level (1-10): The stress level values are normalized between 0.0000 and 1.0000, representing the relative intensity of stress on a standardized scale. Negative Interactions: Normalized values for negative interactions vary from 0.4000 to 1.0000, indicating the proportion of reported negative interactions relative to the maximum reported value. By normalizing the data, all variables are transformed into a comparable range, facilitating a more straightforward comparison of their impacts on human behavior. This process is particularly useful when variables have different units or scales, allowing for a more meaningful analysis of their relationships.

**TABLE 3.** Deviation sequence

| Deviation sequence | | | |
|---|---|---|---|
| **Income** | **Physical Activity (hours/week)** | **Stress Level (1-10)** | **Negative Interactions** |
| 0.9722 | 0.5000 | 0.0000 | 0.4000 |
| 0.0000 | 0.8333 | 1.0000 | 1.0000 |
| 1.0000 | 0.0000 | 0.2500 | 0.0000 |
| 0.9167 | 1.0000 | 0.7500 | 0.6000 |
| 0.9583 | 0.6667 | 0.5000 | 0.2000 |

Table 3 shows the explanation of deviation sequence 1. Income: The first column represents the deviation in income. Each value indicates how much the income deviates from a reference point. For example, a value of 0.9722 suggests an income that is higher than the reference, while a value of 0.0000 indicates no deviation. 2. Physical Activity (hours/week): The second column represents the deviation in physical activity, measured in hours per week. A value of 0.5000, for instance, suggests an increase in physical activity compared to the reference.3. Stress Level (1-10): The third column represents the deviation in stress level, measured on a scale from 1 to 10. A value of 1.0000 indicates the maximum deviation, meaning the stress level is at its highest. 4. Negative Interactions: The fourth column represents the deviation in negative interactions. This could refer to the number or intensity of negative social interactions. A value of 1.0000 suggests the maximum deviation, indicating a high level of negative interactions. Looking at the deviation sequence, it seems that each row represents a different scenario or individual, and the values indicate how each factor deviates from a certain baseline or reference point. For example, the second row has a high deviation in stress level (1.0000) and negative interactions (1.0000), suggesting a scenario with high stress and a lot of negative social interactions. The fourth row has high deviations in income (0.9167) and physical activity (1.0000), indicating a higher income and increased physical activity compared to the reference.

**TABLE 4.**Grey relation coefficient

| Income | Physical Activity (hours/week) | Stress Level (1-10) | Negative Interactions |
|---|---|---|---|
| 0.3396 | 0.5000 | 1.0000 | 0.5556 |
| 1.0000 | 0.3750 | 0.3333 | 0.3333 |
| 0.3333 | 1.0000 | 0.6667 | 1.0000 |
| 0.3529 | 0.3333 | 0.4000 | 0.4545 |
| 0.3429 | 0.4286 | 0.5000 | 0.7143 |

Table 4 shows explanation of GRC Income: The grey relation coefficient for income ranges from 0.3396 to 1.0000. These coefficients reflect the relative importance or similarity of each individual's income compared to others in the dataset. Physical Activity (hours/week): Coefficients for physical activity range from 0.3750 to 1.0000. Higher coefficients suggest a closer relationship or similarity in terms of physical activity levels between individuals. Stress Level (1-10): The grey relation coefficients for stress level vary from 0.3333 to 1.0000. Higher coefficients indicate a higher degree of similarity in stress levels between individuals. Negative Interactions: Coefficients for negative interactions range from 0.3333 to 1.0000. These values signify the degree of similarity in reported negative interactions among individuals. In Grey System Theory, the grey relation coefficient helps identify patterns or relationships by evaluating the proximity of data points. Higher coefficients suggest a stronger relationship or similarity between variables. This approach is particularly useful when dealing with complex systems where precise mathematical relationships are difficult to define.

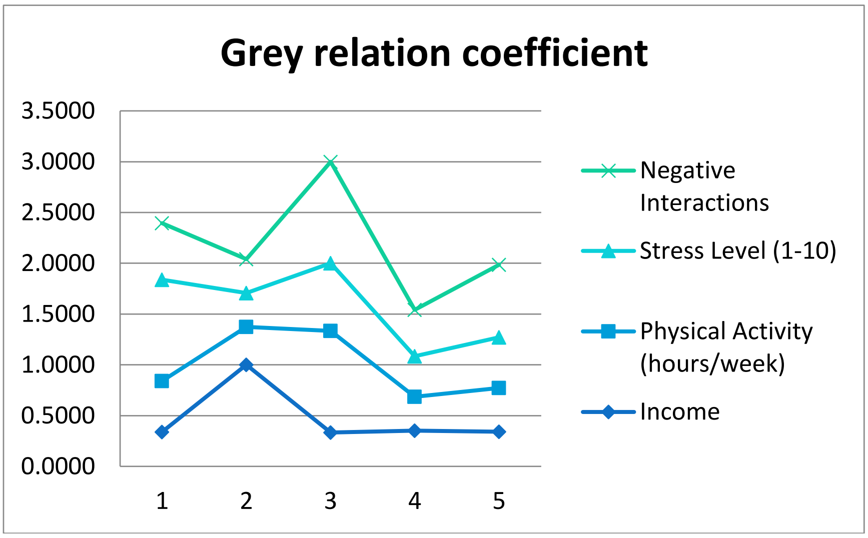


**FIGURE 3.**Grey relation coefficient

Figure 3 illustrate the graphical representation of Grey relation coefficient

**TABLE 5.**G R G

| Age | GRG |
|---|---|
| 28.00 | 0.5988 |
| 35.00 | 0.5104 |
| 22.00 | 0.7500 |
| 45.00 | 0.3852 |
| 30.00 | 0.4964 |

In the above table 5 shows GRG 22 has high and 45 has low 28 has 0.5988, 30 has 0.4964 and 35 has 0.5104.

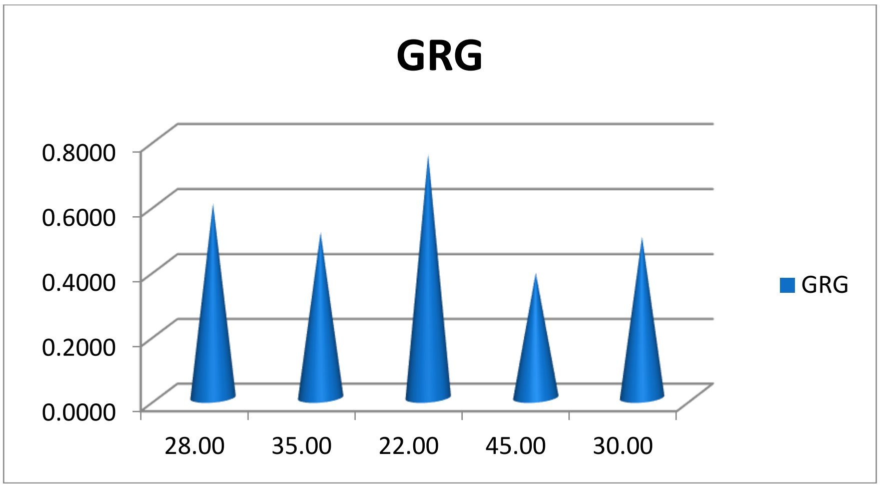


**FIGURE 4.**GRG

In the above figure 4 shows GRG 22 has high and 45 has low.

**TABLE 6.** Rank

| Age | Rank |
|---|---|
| 28 | 2 |
| 35 | 3 |
| 22 | 1 |
| 45 | 5 |
| 30 | 4 |

In this Table 5 22 is ranked at first position and 45 is ranked at fifth position.

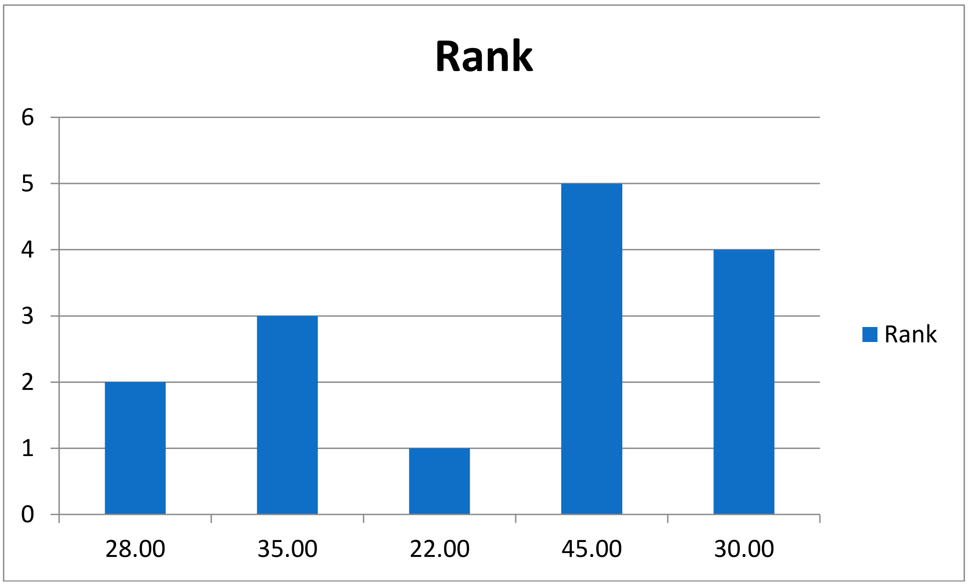


**FIGURE 5.** Rank

In this figure 5 age 22 is ranked at first position and age 45 is ranked at fifth position.

# 4. CONCLUSION

Human behavior analysis using machine learning presents a dynamic and impactful approach to understanding and interpreting various facets of human actions. The integration of machine learning techniques facilitates nuanced insights into patterns, correlations, and predictive behaviors. By leveraging algorithms to process diverse data sources such as age, income, physical activity, stress levels, and negative interactions, researchers and practitioners can derive valuable information for applications ranging from personalized healthcare to social dynamics. However, challenges persist, including the need for robust models, ethical considerations, and the interpretability of machine-generated results. Advancements in this field hold the potential to enhance our understanding of human behavior and inform interventions for improved well-being and decision-making.

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