Healthy Food: Motivational factors behind BMI objectives

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I. Introduction

Body Mass Index (BMI) serves as a crucial metric in evaluating individual health by providing a straightforward indicator of body fatness. The motivations driving individuals to pursue specific BMI objectives are multifaceted, encompassing health, aesthetic, and societal factors. [1]

Health concerns, such as the prevention of chronic diseases, including diabetes, cardiovascular disease, and hypertension, frequently underpin the drive to achieve an optimal BMI. Aesthetic considerations also significantly influence this pursuit, as societal beauty standards and personal self-esteem play a pivotal role in shaping body image goals. Furthermore, social influences, including peer dynamics and media portrayals, reinforce the importance of maintaining a desirable BMI.

Professional demands in fields such as athletics, modeling, and the performing arts often necessitate adherence to specific BMI ranges to meet career standards. Psychological motivations, including the quest for self-improvement and the achievement of personal milestones, further propel individuals toward managing their BMI. Educational initiatives that highlight the advantages of a healthy BMI can also inspire lifestyle adjustments aimed at achieving these goals.

Additionally, familial and cultural expectations can significantly impact attitudes towards body weight and health, thereby influencing BMI-related ambitions. The convergence of these diverse factors underscores the complexity of the motivations behind the BMI objectives, highlighting the need for a comprehensive approach to understanding and supporting individuals in their efforts to achieve optimal health outcomes.

II. Related works

A. Definition of BMI

The Body Mass Index (BMI) was developed in the early 19th century by the Belgian mathematician and statistician Adolphe Quetelet, and hence it was initially known as the Quetelet Index. It became widely known as BMI in the 1970s when it was recognized by the World Health Organization (WHO) as a useful tool for population health assessments.

BMI is used as a screening tool to categorize individuals into different weight status categories that can help assess whether they are underweight, normal weight, overweight, or obese. BMI provides an indirect measure of body fat, which can help gauge potential health risks associated with different body weights.

BMI is a widely accepted method because it is simple, quick, and inexpensive to use in both clinical and non-clinical settings. However, it does not directly measure body fat percentage and may not accurately reflect an individual's health status, particularly in athletes or those with high muscle mass. Despite its limitations, BMI remains a valuable starting point for identifying potential weight-related health problems and guiding further diagnostic evaluations. [2]

B. Calculation and Classification of BMI

BMI, or Body Mass Index, is a measure used to determine if a person has a healthy body weight for their height. It is calculated by taking a person's weight in kilograms and dividing it by their height in meters squared. This provides a single number that can help assess whether an individual is underweight, normal weight, overweight, or obese.

For example, an adult who weighs 72 kg and whose height is 1.74 m:

- **Square the height**: 1.74×1.74=3.0276
- **Dividing**:BMI=72/3.0276
- **Perform the division**: BMI=23.78

BMI	Nutritional status
Below 18.5	Underweight
18.5–24.9	Normal weight
25.0–29.9	Pre-obesity
30.0–34.9	Obesity class I
35.0–39.9	Obesity class II
Above 40	Obesity class III

Fig. 1. Nutritional Status [3]

C. Advantages and Limitations of BMI

Advantages of BMI:

- Standardization: BMI provides a standardized method to classify individuals weight status. It is recognized and used globally, facilitating comparisons across different populations and studies.
- Ease of Use: BMI requires only weight and height, which are easily obtainable measurements that can be taken with minimal equipment. A standard scale and a tape measure are all that is needed, both of which are commonly found in homes, schools, and healthcare facilities. The formula itself is straightforward—weight in kilograms divided by height in meters squared (kg/m^2)—and can be calculated manually or with a basic calculator. Additionally, numerous online tools and smartphone apps are available to perform this calculation instantly, making it even more accessible.
- Cost-Effective: Unlike other body composition measurements that may require expensive devices (e.g., DEXA scans, bioelectrical impedance analysis), BMI can be calculated without any special tools, making it a more accessible and cost-effective method for assessing body weight relative to height. This simplicity allows individuals, healthcare providers, and researchers to quickly obtain a general indication of whether a person falls within a healthy weight range.
  The calculation only requires basic measurements of height and weight, which can be easily obtained with a standard scale and a tape measure, further enhancing its practicality for widespread use in various settings.
- Public Awareness and Education: The widespread use of BMI has played a significant role in raising public awareness about the importance of maintaining a healthy weight. By simplifying the concept of body weight assessment, BMI has made it easier for people to understand the potential health risks associated with being overweight or underweight.
  Educational campaigns often use BMI to highlight the link between body weight and chronic diseases such as diabetes, heart disease, and hypertension. Preventive health programs leverage BMI to educate people on healthy lifestyle choices, promoting balanced diets and regular physical activity. This widespread understanding encourages individuals to monitor their own BMI, fostering a proactive approach to health and well-being.
- Baseline for Further Evaluation: BMI, while not a comprehensive measure of body composition, serves as a useful baseline that can prompt further evaluation and more detailed assessments if necessary. For instance, a high or low BMI can signal the need for additional diagnostic tests such as body fat percentage analysis, waist-to-hip ratio, or skinfold measurements.
  These additional assessments provide a more nuanced understanding of an individual's health, considering factors like muscle mass, bone density, and fat distribution. Consequently, healthcare providers can develop more personalized and effective treatment plans based on a comprehensive evaluation of the patient's overall health status.
- Track Population Health Trends: BMI data is instrumental in tracking population health trends over time. Public health officials use aggregated BMI data to monitor the prevalence of obesity and underweight conditions within different demographics, regions, and over various periods. This information helps identify at-risk populations and evaluate the effectiveness of public health interventions. For example, if a rise in obesity rates is detected, health authorities can implement targeted initiatives such as nutrition education, community exercise programs, and policy changes to address the issue.
  Moreover, tracking these trends aids in resource allocation, ensuring that healthcare resources are directed towards areas with the greatest need.
- Quick Screening Tool: In clinical settings, BMI is used as a quick and efficient initial screening tool to identify potential health issues related to body weight. During routine check-ups, healthcare providers can calculate a patient's BMI in seconds, providing immediate insight into whether the patient falls within a healthy weight range.
  If the BMI indicates underweight, overweight, or obesity, the healthcare provider can promptly initiate further assessments and discussions about diet, exercise, and other lifestyle factors. This rapid screening facilitates early detection and intervention, helping to prevent the development of weight-related health conditions before they become severe. By incorporating BMI into regular health assessments, clinicians can ensure timely and effective management of their patients' overall health.

Limitations of BMI:

- Age: BMI is a measure that calculates an individual's body weight relative to their height, but it does not account for changes in body composition that typically occur with aging. As individuals age, they often experience a gradual loss of muscle mass, a condition known as sarcopenia, while their body fat tends to increase. This shift in body composition can lead to an increase in overall fat mass even if the BMI remains relatively low.
  Consequently, an older adult may have a lower BMI that does not accurately reflect their higher fat mass or the decreased muscle mass, potentially leading to a misinterpretation of their health status. Therefore, while BMI is a useful general indicator of body weight, it may not fully capture the nuances of body composition in older populations, who may be at risk of obesity or malnutrition despite a normal or low BMI.
- Fat Distribution: BMI is a metric that provides an estimate of body weight relative to height, but it does not provide information about the distribution of fat within the body.

Specifically, BMI cannot distinguish between different types of body fat, such as abdominal (visceral) fat versus peripheral (subcutaneous) fat. Research indicates that abdominal fat, particularly visceral fat—which accumulates around internal organs such as the liver, pancreas, and intestines—is associated with a higher risk of various health conditions. This type of fat is metabolically active and has been linked to increased risks of cardiovascular diseases, type 2 diabetes, hypertension, and other metabolic disorders.
In contrast, peripheral fat, which is stored in the limbs and subcutaneous tissues, is generally considered less harmful in terms of health risks. Thus, while BMI provides a general indication of body weight, it does not reflect the critical aspect of fat distribution, which can have a significant impact on an individual's overall health and risk profile. Therefore, additional measures such as waist circumference, waist-to-hip ratio, or imaging techniques may be necessary to assess the distribution of fat and provide a more comprehensive evaluation of health risks.

- Body Composition: BMI is a metric that calculates an individual's body weight in relation to their height, but it does not differentiate between muscle mass and fat mass. As a result, individuals with a high proportion of muscle mass, such as athletes or bodybuilders, may have a high BMI despite possessing a relatively low percentage of body fat. This is due to the fact that muscle tissue is denser and weighs more than fat tissue.
  Consequently, such individuals may be misclassified as overweight or obese according to BMI standards, even though their body fat percentage is low and their overall health may be optimal. Therefore, while BMI can serve as a general indicator of body weight, it does not provide a precise measure of body composition. More accurate assessments of body composition, such as body fat percentage measurements, dual-energy X-ray absorptiometry (DXA), or bioelectrical impedance analysis (BIA), are necessary to better understand an individual's body fat and muscle distribution and to avoid potential misclassification based on BMI alone.
- Not Suitable for All Populations: BMI may not be a good indicator of health for specific groups. For instance, elderly individuals often experience a loss of muscle mass with aging, which can lead to a higher body fat percentage that BMI does not reflect. In children and adolescents, BMI does not adjust for growth patterns and changes in body composition during development. For these reasons, specialized growth charts or other methods are often used for younger populations, and adjustments or alternative measurements may be necessary for older adults.
- Cultural and Genetic Differences: BMI does not account for genetic and cultural differences that affect body composition. Different ethnic groups might have different fat distribution patterns and body shapes. For instance, studies have shown that Asians might have higher body fat percentages at lower BMI levels compared to Europeans. Such variations can make BMI less accurate when applied across diverse populations, necessitating adjustments or alternative measures for more precise health assessments.

D. *Motivational Factors Behind Dietary Changes*

Intrinsic Motivation:

- Health Improvement: Desire to avoid diseases and improve overall well-being.
- Increased Energy: Seeking better physical performance and mental clarity.
- Self-Esteem: Improving body image and self-confidence.

Extrinsic Motivation:

- Social Pressures: Influence from peers, family, and societal standards.
- Medical Advice: Recommendations from healthcare professionals to avoid or manage health issues.
- Incentives such as monetary rewards, recognition, or achieving personal milestones.

Motivational Factors:

- Behavioral Change: The underlying psychological drivers that influence a person's decision to adopt healthier eating habits.

E. *Correlation Between Motivation and BMI*

Research Findings:

- Intrinsic Motivation: Studies indicate that individuals with intrinsic motivations, such as personal health goals, have better long-term weight management and lower BMI.
  Example: A study by Teixeira et al. (2012) found that intrinsic motivation predicted better adherence to weight loss programs.[4]
- Extrinsic Motivation: While effective in the short term, extrinsic motivations may not sustain long-term dietary changes.
  Example: A meta-analysis by Ng et al. (2012) revealed that external rewards and social pressures were less effective in maintaining long-term weight loss.[5]

III. Methods/ Main part

A. *Calculation of BMI Values*

```python
# Display the first few rows of the DataFrame
print("Initial DataFrame:")
print(df.head())

# Assuming the columns for height and weight are named 'Height' and 'Weight'
# Height is in meters and weight is in kilograms

# Calculate the BMI and add it as a new column
df['BMI'] = df['weight'] / (df['height'] ** 2)

# Display the DataFrame with the new BMI column
print("DataFrame with BMI column:")
print(df.head())

# Save the updated DataFrame back to a CSV file (optional)
output_file_path = 'Downloads/seminar_files (2)/seminar_files/anonymized_user_profile_with_bmi.csv'
df.to_csv(output_file_path, index=False)

print(f"Updated DataFrame saved to {output_file_path}")
```

Fig. 2. Calculation of BMI Values

The figure first displays the initial few rows of a DataFrame, then calculates the Body Mass Index (BMI) using the columns 'Height' (in meters) and 'Weight' (in kilograms), adding the BMI as a new column to the DataFrame. It then shows the updated DataFrame with the new BMI column and saves this modified DataFrame to a specified CSV file, printing the file path to confirm the save location.

B. Intrinsic Motivation - BarPlot Chart

In this section, the barplot graph of the M1, M2, M3, and M4 values in the intrinsic motivation is drawn. In the graphs, the x-axis indicates the category of the answers given in the collected data, while the y-axis shows the total piece.

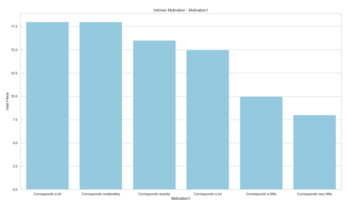

Fig. 3. Intrinsic Motivation-M1

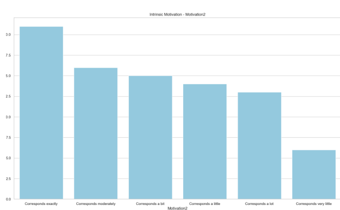

Fig. 4. Intrinsic Motivation-M2

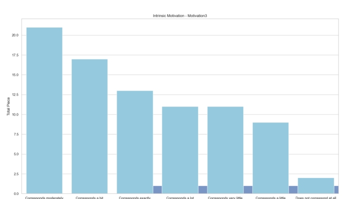

Fig. 5. Intrinsic Motivation-M3

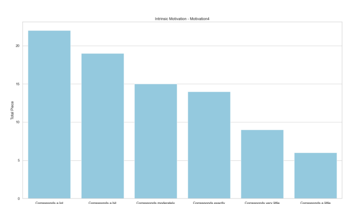

Fig. 6. Intrinsic Motivation-M4

A bar plot chart is a versatile graphical representation used to compare different categories or groups through rectangular bars, where the length of each bar is proportional to the value it represents. The bars can be plotted either vertically or horizontally, making it adaptable to various types of data presentations. This type of chart is particularly effective for illustrating differences among discrete categories, making it a staple in business, research, and educational settings. Each bar represents a category, and the height or length corresponds to the category's value, allowing for quick visual comparison. Grouped bar plots can display multiple data sets side-by-side, facilitating comparisons between different groups or over time. Stacked bar plots, on the other hand, show the cumulative effect of several categories, illustrating the composition of the whole. One of the key advantages of bar plots is their simplicity and clarity, which makes them easy to read and interpret. Colors or patterns can be used to distinguish different bars, adding an additional layer of visual differentiation. Bar plots can also incorporate error bars to indicate variability or uncertainty in the data, providing a more comprehensive understanding of the results. Despite their simplicity, bar plots can convey complex data in an accessible and engaging way, making them an essential tool for data visualization. Proper labeling of axes and bars ensures that the chart is informative and meaningful to the audience. Overall, bar plots are a fundamental tool for presenting categorical data in a clear, concise, and visually appealing manner.[6]

C. Integrated Regulation - Pie Chart

In this section, pie charts of the integration motivation elements M5, M6, M7 and M8 values were drawn and their distributions were calculated.

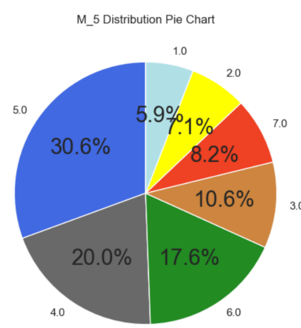

Fig. 7. Integrated Regulation-M5

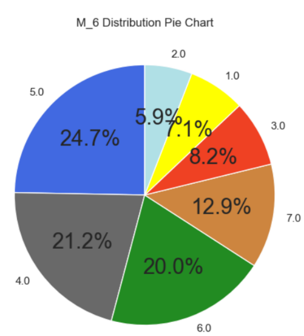

Fig. 8. Integrated Regulation-M6

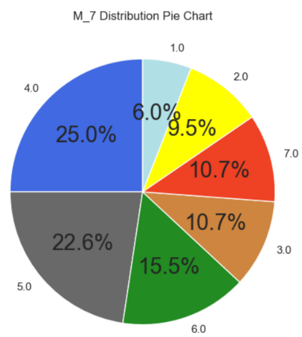

Fig. 9. Integrated Regulation-M7

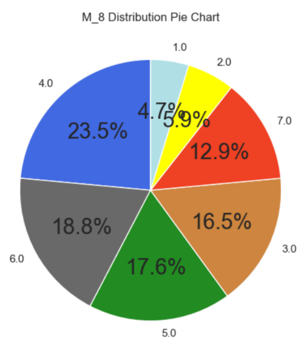

Fig. 10. Integrated Regulation-M8

A pie chart is a circular statistical graphic divided into slices to illustrate numerical proportions, where each slice represents a category's contribution to the whole. The entire pie signifies 100 of the data set, making it easy to visualize how individual parts contribute to the overall total. Commonly used in business and media for their straightforward and visual appeal, pie charts are ideal for displaying percentage or proportional data, especially when comparing a small number of categories (typically fewer than six). Overcrowding with too many slices can reduce readability and effectiveness. Differentiating slices by colors or patterns enhances visual accessibility, and labels or legends can provide additional context and clarity.[6]

D. Correlation Matrix and Heatmap Between Age and BMI

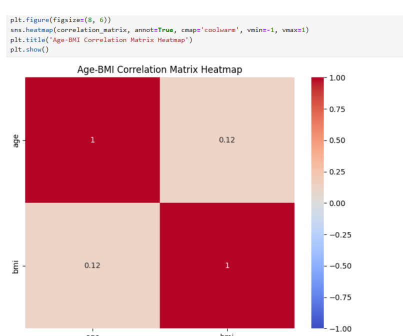

Fig. 11. Age-BMI Correlation Matrix Heatmap

The code generates a heatmap using Seaborn and Matplotlib to visualize the correlation matrix between 'age' and 'BMI'. The heatmap, titled the "Age-BMI Correlation Matrix Heatmap", displays the correlation values with annotations, using the "coolwarm" color map. The plot shows a weak positive correlation (0.12) between 'age' and 'BMI', indicating a slight tendency for BMI to increase with age. The diagonal values (1.0) represent the perfect correlation of each variable with itself.

E. Intrinsic Motivation and BMI Correlation Matrix Heatmap

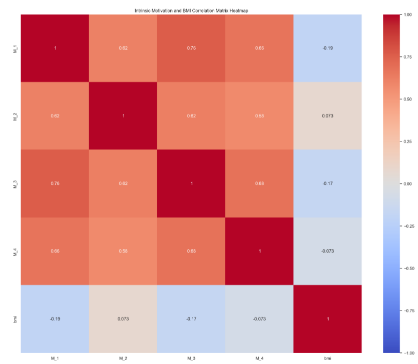

Fig. 12. Intrinsic Motivation and BMI Correlation Matrix Heatmap

The visual representation in the heatmap shows the strength and direction of the relationships between different intrinsic motivation factors and BMI. From the data, it can be inferred that intrinsic motivations (M1, M2, M3, M4) generally have weak correlations with BMI, with the highest absolute correlation being -0.19 for M1.

F. Correlation Between Motivation and Age-BMI

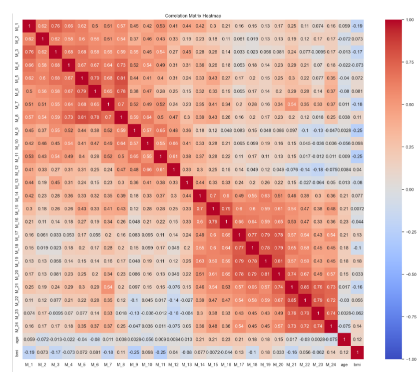

Fig. 13. Motivation and Age Heatmap

- This image shows a correlation matrix heatmap, which visualizes the relationships between multiple variables. The matrix is symmetrical, with variable names listed along both axes. Each cell represents the correlation coefficient between two variables, ranging from -1 to 1.
- The color scheme uses red for positive correlations, blue for negative correlations, and white for near-zero

correlations. Darker shades indicate stronger correlations. Most correlations in this matrix appear to be positive, as evidenced by the prevalence of red and pink colors. The diagonal of the matrix shows perfect correlations of 1, as each variable correlates perfectly with itself.

- Correlations generally range from weak to moderate (between 0.2 and 0.7).
- The strongest correlations are observed between M5 and M6 (0.79), M5 and M8 (0.81), and M15 and M16 (0.79).
- There are also relatively strong correlations among M21, M22, M23, and M24 (ranging from 0.7 to 0.85).
- The strongest correlation with BMI is M6 (-0.081), very weak and negative.
- The strongest negative correlation is between BMI and M3 (-0.17), which is still a weak relationship.
- Although there is a general relationship between variables, the absence of very strong correlations suggests that each variable carries distinct information.

IV. Evaluation

A. Pearson Test Between Age And BMI

```
]: import pandas as pd
   from scipy.stats import pearsonr
   df = pd.read_csv('anonymized_user_profile.csv')

   age = df['age']
   bmi = df['bmi']

   df_clean = df.dropna(subset=['age', 'bmi'])

   age_clean = df_clean['age']
   bmi_clean = df_clean['bmi']

   correlation, p_value = pearsonr(age_clean, bmi_clean)

   print(f"Pearson correlation coefficient: {correlation}")
   print(f"P-value: {p_value}")

   Pearson correlation coefficient: 0.11921947681384855
   P-value: 0.18541947759116545

]:
```

Fig. 14. Pearson Test Between Age And BMI [3]

- The code begins by importing pandas for data manipulation and pearsonr from scipy.stats for correlation calculation. It then reads a CSV file named 'anonymized-user-profile.csv' into a DataFrame df. The 'age' and 'BMI' columns are extracted into separate variables. To handle missing data, it drops any rows where either 'age' or 'BMI' is missing, creating a cleaned DataFrame df-clean. From this cleaned DataFrame, it again extracts the 'age' and 'BMI' columns into age-clean and bmi-clean variables. The Pearson correlation coefficient and the corresponding p-value are then calculated using pearsonr for these cleaned columns.
- The Pearson correlation coefficient between age and bmi is approximately 0.1192. This value indicates a very weak positive linear relationship between the age and BMI of the individuals in the data set.
- The p-value is approximately 0.1854. Since the p-value is greater than 0.05, we cannot reject the null hypothesis that there is no linear correlation between age and BMI.
- There is no significant linear relationship between age and BMI in the data set.

B. Spearman Correlation Between Intrinsic Motivation and BMI

```
[135]: import pandas as pd
       import scipy.stats as stats

       df1 = pd.read_csv('anonymized_user_profile.csv')
       df2 = pd.read_csv('user_additional_profile.csv')

       m_columns = [f'M_{i}' for i in range(1, 5)]
       bmi = df1['bmi']

       df2_cleaned = df2.dropna(subset=m_columns)
       bmi_cleaned = bmi.dropna()

       df_combined = df2_cleaned.join(bmi_cleaned, how='inner')

       print("Relation between Intrinsic Motivation Values and BMI")

       for col in m_columns:
           correlation, p_value = stats.spearmanr(df_combined[col], df_combined['bmi'])
           print(f"Spearman correlation coefficient ({col} and BMI): {correlation}")
           print(f"P-value: {p_value}")
           print()

       Relation between Intrinsic Motivation Values and BMI
       Spearman correlation coefficient (M_1 and BMI): -0.12420592536759786
       P-value: 0.2754490842598613

       Spearman correlation coefficient (M_2 and BMI): -0.001618177679759785
       P-value: 0.9887075699687036

       Spearman correlation coefficient (M_3 and BMI): -0.1123029091120331
       P-value: 0.3244366762891192

       Spearman correlation coefficient (M_4 and BMI): -0.0896801062377661
       P-value: 0.4318823054791582
```

Fig. 15. Spearman Correlation Between Intrinsic Motivation and BMI

The results indicate that there are no significant correlations between any of the intrinsic motivation values (M1, M2, M3, M4) and BMI. All the correlation coefficients are very close to zero, and the p-values are well above the 0.05 threshold for statistical significance. This suggests that intrinsic motivation values, measured by M1, M2, M3, and M4, do not have a significant relationship with BMI in the data set.

C. Spearman Correlation Between Integrated Regulation and BMI

The results indicate that there are no significant correlations between the integrated regulation values (M5, M6, M7, M8) and BMI. All the correlation coefficients are very close to zero, and the p-values are well above the 0.05 threshold for statistical significance. This suggests that these integrated regulation values, measured by M5, M6, M7, and M8, do not have a significant relationship with BMI in the dataset.

```
Relation between Integrated Regulation Values and BMI
Spearman correlation coefficient (M_5 and BMI): -0.11058216054694978
P-value: 0.3319522560985575

Spearman correlation coefficient (M_6 and BMI): -0.011468124908127365
P-value: 0.9200986156628184

Spearman correlation coefficient (M_7 and BMI): 0.033295220422087955
P-value: 0.7708232655245539

Spearman correlation coefficient (M_8 and BMI): -0.09844370987286692
P-value: 0.3880608104232105
```

Fig. 16. Spearman Correlation Between Integrated Regulation and BMI

D. Spearman Correlation Between Identified Regulation and BMI

The results indicate that there are no significant correlations between the identified regulation values (M9, M10, M11, M12) and BMI. Although M11 shows a weak negative correlation that is close to statistical significance (p = 0.058), it still does not meet the threshold (p ¡ 0.05). Therefore, these identified regulation values, measured by M9, M10, M11, and M12, do not have a significant relationship with BMI in the data set.

```
Relation between Identified Regulation Values and BMI
Spearman correlation coefficient (M_9 and BMI): -0.09315987518419805
P-value: 0.41722299705386556

Spearman correlation coefficient (M_10 and BMI): 0.04467859234982216
P-value: 0.6977096883403477

Spearman correlation coefficient (M_11 and BMI): -0.21592176384644632
P-value: 0.0576113255660357

Spearman correlation coefficient (M_12 and BMI): -0.10565473164638112
P-value: 0.3572424328566124
```

Fig. 17. Spearman Correlation Between Identified Regulation and BMI

E. Spearman Correlation Between Introjected Regulation and BMI

The results indicate that there are no significant correlations between the introjected regulation values (M13, M14, M15, M16) and BMI. All the correlation coefficients are very close to zero, and the p-values are well above the 0.05 threshold for statistical significance. This suggests that these introjected regulation values, as measured by M13, M14, M15, and M16, do not have a significant relationship with BMI in the dataset.

```
Relation between Introjected Regulation Values and BMI
Spearman correlation coefficient (M_13 and BMI): 0.0688550634597514
P-value: 0.5465361609451266

Spearman correlation coefficient (M_14 and BMI): 0.06627254318501766
P-value: 0.5617171223385794

Spearman correlation coefficient (M_15 and BMI): 0.041767286795840214
P-value: 0.714754543498884

Spearman correlation coefficient (M_16 and BMI): 0.0789649678779899
P-value: 0.4890941783797049
```

Fig. 18. Spearman Correlation Between Introjected Regulation and BMI

F. Spearman Correlation Between External Regulation and BMI

The results indicate that there are no significant correlations between the external regulation values (M17, M18, M19, M20) and BMI. All the correlation coefficients are very close to zero, and the p-values are well above the 0.05 threshold for statistical significance. This suggests that these external regulation values, as measured by M17, M18, M19, and M20, do not have a significant relationship with BMI in the dataset.

```
Relation between External Regulation Values and BMI
Spearman correlation coefficient (M_17 and BMI): 0.08231903909307292
P-value: 0.4678821574923804

Spearman correlation coefficient (M_18 and BMI): 0.03993727390587048
P-value: 0.72504206583955

Spearman correlation coefficient (M_19 and BMI): 0.01499853721097156
P-value: 0.8949470711469504

Spearman correlation coefficient (M_20 and BMI): 0.06008576229823158
P-value: 0.5964975575488279
```

Fig. 19. Spearman Correlation Between External Regulation and BMI

G. Spearman Correlation Between Amotivation and BMI

```
Relation between Amotivation and BMI
Spearman correlation coefficient (M_21 and BMI): 0.13725088216978815
P-value: 0.23080923716591883

Spearman correlation coefficient (M_22 and BMI): 0.15029727507577484
P-value: 0.18903692174299774

Spearman correlation coefficient (M_23 and BMI): 0.19785522390901503
P-value: 0.08249167333024023

Spearman correlation coefficient (M_24 and BMI): 0.1856816547886621
P-value: 0.10360810697151027
```

Fig. 20. Spearman Correlation Between Amotuvation and BMI

- This image presents statistical results showing the relationship between amotivation and BMI using Spearman correlation coefficients. Four different measures (M21, M22, M23, and M24) are correlated with BMI, each yielding a correlation coefficient and corresponding p-value. The Spearman correlation coefficients range from approximately 0.137 to 0.198, indicating weak positive correlations between the amotivation measures and BMI.
- The p-values range from about 0.082 to 0.238, with none falling below the common significance threshold of 0.05. This suggests that while there are slight positive relationships between the amotivation measures and BMI, these correlations are not statistically significant at the conventional 0.05 level. The strongest correlation is observed for M23 (coefficient = 0.198, p-value = 0.082), which is closest to achieving statistical significance.
- These results indicate a trend towards a weak positive relationship between amotivation and BMI, but the evidence is not strong enough to conclude a definitive, statistically significant association based on these particular measures and the chosen significance threshold.
- M21 and BMI: The correlation coefficient is 0.137 with a p-value of 0.231, indicating a weak positive correlation.
- M22 and BMI: The correlation coefficient is 0.150 with a p-value of 0.189, indicating a slightly stronger weak positive correlation.
- M23 and BMI: The correlation coefficient is 0.198 with a p-value of 0.082, suggesting a potential trend towards significance.
- M24 and BMI: The correlation coefficient is 0.186 with a p-value of 0.104, similar to M23, indicating a trend towards positive correlation but not statistically significant.

V. CONCLUSION

- According to the data information given, the relationship between motivation values and BMI was evaluated and tried to be explained.
- In general, the analysis indicates that there is **no significant relationship** between various motivation values (intrinsic, integrated, identified, introjected, external, amotivation) and BMI in the data set. Most of the correlation coefficients were close to zero and none of the p values reached the conventional threshold for statistical significance (p ¡ 0.05). The findings suggest that factors other than motivation values might be more influential in determining BMI.
- For the Age-BMI values, there is no significant linear relationship between age and BMI in dataset.
- The motivational factors behind BMI objectives are multifaceted and deeply intertwined with individual goals, societal influences, and health considerations. For many, achieving a specific BMI can represent a significant

milestone in their journey towards improved health and well-being, serving as a tangible goal that drives lifestyle changes and fosters a sense of accomplishment. These objectives are often influenced by personal aspirations for better physical fitness, increased self-esteem, and a desire for longevity and quality of life.

A. Future Directions

- Further research is needed to explore the complex interactions between different types of motivation and BMI.
- Development of personalized motivational strategies to promote healthy eating behaviors.
- Future research on the motivational factors behind BMI objectives should focus on several key areas to enhance our understanding and improve interventions. Exploring the role of intrinsic and extrinsic motivation in achieving and maintaining healthy BMI levels across diverse populations can reveal critical insights into tailored strategies. Longitudinal studies that track motivational changes over time in relation to BMI can help identify patterns and predict long-term success in weight management programs. Investigating the influence of psychological factors such as self-efficacy, body image, and mental health on motivation and BMI can provide a more holistic view of the challenges individuals face.
- The impact of cultural, socioeconomic, and environmental factors on motivation should be examined to develop culturally sensitive and inclusive interventions. Advances in technology, such as mobile health applications and wearable devices, offer new opportunities to monitor and enhance motivation in real-time. Their effectiveness in promoting sustained healthy behaviors warrants thorough investigation. Understanding the role of social support systems, including family, friends, and online communities, in fostering motivation and achieving BMI objectives can inform the design of comprehensive support networks.
- Experimental studies that test different motivational strategies, such as goal setting, feedback, and rewards, can identify the most effective approaches for various demographics. Integrating interdisciplinary perspectives from psychology, nutrition, and behavioral science will be crucial in developing robust, evidence-based interventions. Addressing these future directions can contribute to more effective, personalized, and sustainable solutions for achieving healthy BMI and overall well-being.[6]

REFERENCES

[1] F. Q. Nuttall, “Body Mass Index,” Nutrition Today, vol. 50, no. 3, pp. 117–128, Apr. 2015.

[2] CDC, “About Body Mass Index (BMI),” BMI, Jul. 01, 2024.

[3] World Health Organization, “A healthy lifestyle - WHO recommendations,” World Health Organisation, May 06, 2010.

[4] P. J. Teixeira, E. V. Carraça, D. Markland, M. N. Silva, and R. M. Ryan, “Exercise, Physical activity, and self-determination theory: a Systematic Review,” International Journal of Behavioral Nutrition and Physical Activity, vol. 9, no. 1, p. 78, Jun. 2012.

[5] J. Y. Y. Ng et al., “Self-Determination Theory Applied to Health Contexts,” Perspectives on Psychological Science, vol. 7, no. 4, pp. 325–340, Jun. 2012.

[6] OpenAI, “ChatGPT ,” ChatGPT, 2024.

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