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Article

Predicting control loss in eating behaviors using decision tree regression: Implications for educational interventions targeting motivational and physical factors

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Abstract: This study explores the determinants of control loss in eating behaviors, employing decision tree regression analysis on a sample of 558 participants. Guided by Self-Determination Theory, the findings highlight amotivation ($\beta = 0.48$, $p < 0.001$) and external regulation ($\beta = 0.36$, $p < 0.01$) as primary predictors of control loss, with introjected regulation also playing a significant role ($\beta = 0.24$, $p < 0.05$). Consistent with Self-Determination Theory, the results emphasize the critical role of autonomous motivation and its deficits in shaping self-regulation. Physical characteristics, such as age and weight, exhibited limited predictive power ($\beta = 0.12$, $p = 0.08$). The decision tree model demonstrated reliability in explaining eating behavior patterns, achieving an R^2 value of 0.39, with a standard deviation of 0.11. These results underline the importance of addressing motivational deficits in designing interventions aimed at improving self-regulation and promoting healthier eating behaviors.

Keywords: control loss; eating behaviors; decision tree regression; motivation; Self-Determination Theory; external regulation

1. Introduction

Eating behaviors and the factors that influence them have garnered considerable research interest, as they are critical in understanding health outcomes and developing effective interventions for healthier lifestyles. Food choices and consumption patterns are influenced by a range of factors, including psychological, social, and environmental drivers (Cardoso et al., 2020; Runcan and Marici, 2023; Runcan et al., 2023). For instance, emotional and motivational factors play a significant role in shaping eating habits and are associated with patterns that range from healthy eating to maladaptive behaviors, such as binge eating or uncontrolled food cravings (Stok et al., 2018). The transition from adolescence to adulthood, in particular, is a critical period marked by shifting eating patterns influenced by increased autonomy, exposure to diverse social influences, and changing health beliefs. Understanding these influences is essential for creating targeted interventions that encourage healthier eating habits and prevent the onset of disordered eating patterns (Stok et al., 2018).

The Health Belief Model (HBM) has been widely applied to explore how perceived susceptibility, severity, benefits, and barriers influence health behaviors, including eating habits (Glick et al., 2024; Wang et al., 2022). This model posits that individuals' beliefs about health risks and benefits play a central role in their decisions to engage in or avoid particular health behaviors. Studies have found that HBM constructs can significantly predict the likelihood of engaging in healthy eating behaviors, as individuals are more likely to consume nutrient-rich foods if they perceive significant health benefits and minimal barriers (Glick et al., 2024). However, HBM has also shown limitations, particularly in cases where emotional and motivational factors drive eating behaviors more than health beliefs alone (Akey et al., 2013; Hepworth and Paxton, 2007). For example, emotional eating is often associated with a need for comfort, stress reduction, or mood regulation, indicating that interventions targeting eating behaviors must also address these underlying emotional drivers (Akey et al., 2013; Grodner, 1991).

The Self-Determination Theory (SDT) offers a complementary framework, emphasizing the role of intrinsic and extrinsic motivations in shaping behavior. According to SDT, individuals who are motivated intrinsically (driven by enjoyment or interest) or identified regulation (driven by the value they place on the behavior) tend to show more sustainable health behaviors (Pelletier et al., 2004). In contrast, amotivation and external regulation (driven by external demands) are associated with lower behavioral persistence and less favorable outcomes (Meule, 2020). Prior research supports that motivational factors, including amotivation, intrinsic motivation, and various forms of regulation, are central to understanding why individuals engage in or avoid certain eating behaviors (Meule, 2020). Specifically, amotivation and external regulation are linked to disordered eating behaviors, while intrinsic and integrated motivations correlate with healthier dietary patterns (Dicu et al., 2024; Rad et al., 2024).

In the context of controlled and uncontrolled eating behaviors, decision tree models can offer a structured approach to identify key predictors and their hierarchical importance. Decision tree regression, which maps relationships between predictor variables and outcomes by dividing data into smaller segments, allows researchers to visualize and interpret how specific factors contribute to complex behaviors (Kofman et al., 2010). This method is particularly effective in uncovering interactions among diverse predictors, including psychological, motivational, and demographic variables, and in elucidating the pathways leading to control loss in eating behaviors. The flexibility and interpretability of decision trees make them suitable for identifying actionable insights that can guide educational and motivational interventions.

Despite extensive research on the factors influencing eating behaviors, there remains a gap in understanding how specific motivational and physical predictors contribute to control loss in eating patterns, particularly through advanced analytical methods like decision tree regression. The decision tree regression approach was selected for its unique ability to uncover hierarchical relationships among predictors, which is particularly relevant in understanding complex behavioral phenomena such as eating behaviors. Unlike linear regression methods that assume a uniform impact of predictors, decision tree regression allows for non-linear and interaction effects to emerge, making it well-suited for behavioral studies where variables often interact in dynamic ways. This method's interpretability is another significant advantage, as it visually represents the relationships between variables, facilitating an understanding of how different levels of motivational constructs (e.g., amotivation, external regulation) influence eating behaviors in a stepwise, hierarchical manner. The use of decision tree regression addresses a noted gap in the literature. While prior research has explored predictors of eating behaviors using traditional statistical models, the non-linear interactions and contextual hierarchies often remain unexplored. This approach provides a robust means of identifying key predictors and their relative importance in a structured manner, offering deeper insights into the mechanisms driving control loss in eating behaviors.

Given these insights, the research question guiding this study is: *What are the motivational and physical predictors of control loss in eating behaviors as identified through decision tree regression, and how can these findings inform educational interventions aimed at enhancing self-regulation and promoting healthier eating patterns*?

Thus, the primary aim of this study is to identify and analyze the motivational and physical predictors associated with control loss in eating behaviors. By employing a decision tree regression model, the study seeks to reveal hierarchical relationships among these predictors, providing a structured approach to understand how specific factors contribute to eating patterns. This analysis aims to bridge existing gaps in the literature by integrating motivational, emotional, and physical variables, offering a more comprehensive model of eating behavior regulation.

This study aims to explore the key factors influencing control loss in eating behaviors, focusing on both motivational and demographic aspects. Guided by Self-Determination Theory, the first objective is to examine how motivational factors such as amotivation, external regulation, and intrinsic motivation impact eating behaviors. Additionally, the study evaluates the role of physical and demographic variables, including weight, age, and income, and their interaction with motivational elements.

Using a decision tree model, the research identifies the relative importance of these predictors, highlighting the factors most strongly associated with control loss. In this study, the dependent variable is control loss in eating behaviors, representing the extent to which individuals experience difficulties in regulating their eating habits. The independent variables used in the decision tree regression model include a range of motivational, physical, and demographic predictors. These are amotivation, external regulation, introjected regulation, intrinsic motivation, identified regulation, preferred food type, integrated regulation, weight, age, height, income, marital status, gender, and meal frequency. These variables offer a holistic framework for examining the factors contributing to control loss in eating behaviors, allowing the model to address both psychological and physiological dimensions that underlie self-regulation challenges.

2. Literature review

Eating behavior is a multifaceted domain influenced by physiological, psychological, and sociocultural factors (Emilien and Hollis, 2017). The regulation of eating behavior has been extensively studied through theoretical models that help elucidate the motivations, beliefs, and attitudes that drive eating habits. Key models applied in eating behavior research include the Health Belief Model (HBM), Self-Determination Theory (SDT), and frameworks focused on psychosocial and emotional influences.

Self-Determination Theory has gained prominence as a framework for understanding eating behaviors due to its emphasis on the role of intrinsic and extrinsic motivation in regulating health-related actions. Recent studies have expanded on the application of SDT to eating behaviors, highlighting its utility in various populations and contexts. For instance, Maillet and Grouzet (2023) demonstrated how SDT can explain transitions in eating behaviors during critical life phases, such as the transition to university, by addressing changes in autonomy and relatedness. Similarly, LaCaille et al. (2020) explored weight changes among emerging adults, revealing that intrinsic motivations significantly influence healthy eating and weight management.

Empirical studies have also extended the application of SDT to diverse sociocultural settings. De Man et al. (2020) tested an SDT-based model of healthy eating in a South African township, emphasizing the role of autonomy-supportive environments in promoting dietary changes. Fernandes et al. (2023) explored the relationship between physical activity and eating behaviors, finding that higher physical activity levels were associated with greater intrinsic motivation for healthy eating, thereby supporting the interconnectedness of health behaviors under the SDT framework. Additional research has examined SDT in the context of ecological and sustainable eating. Gauthier et al. (2022) highlighted how motivations for environmental sustainability and eating regulation intersect to promote ecological eating behaviors. This broadens the scope of SDT, illustrating its relevance beyond personal health goals to global challenges.

Moreover, interventions grounded in SDT principles have proven effective in changing dietary behaviors. Coumans et al. (2022) implemented a web-based intervention combining SDT and motivational interviewing, demonstrating significant improvements in diet and physical activity. Similarly, Hricova et al. (2020) linked SDT to disordered eating, showing that deficits in autonomy and competence are associated with unhealthy eating patterns.

2.1. Health belief model

The Health Belief Model (HBM) provides a framework for understanding health-related behaviors, including eating patterns, based on individual beliefs about health risks and benefits (Wang et al., 2022). Originally developed to explain preventive health behaviors, HBM has been widely adopted to investigate dietary habits and lifestyle choices (Ford et al., 2012; Putterman and Linden, 2004). Key constructs of the HBM include perceived susceptibility, severity, benefits, barriers, and self-efficacy. According to HBM, individuals are more likely to engage in health-promoting behaviors, such as consuming nutrient-rich foods, if they perceive the benefits to outweigh the barriers (Glick et al., 2024). Research has shown that individuals motivated by health considerations are more likely to make sustainable dietary changes, whereas those driven by appearance concerns, such as body image, may engage in short-term, restrictive dieting with limited success (Putterman and Linden, 2004; Irvine et al., 2019).

Studies on HBM in dietary contexts reveal that perceived barriers, such as cost and convenience, significantly impact food choices (Pinho et al., 2018). Additionally, cultural and socioeconomic factors can modulate these beliefs, with social support playing a critical role in overcoming perceived obstacles (Akey et al., 2013). For example, adults who perceive social support are more likely to adopt healthier eating behaviors, highlighting the importance of community and family influences (Ford et al., 2012). Despite the utility of HBM in identifying health-driven eating motivations, the model has limitations in addressing emotional and motivational drivers of eating behaviors, such as cravings and stress eating (Grodner, 1991; Greenbaum, 2018). Therefore, integrating HBM with models that emphasize emotional and motivational regulation is essential for a comprehensive understanding of eating behaviors.

2.2. Self-Determination Theory

Self-Determination Theory (SDT) posits that human motivation exists on a spectrum, ranging from intrinsic (self-driven) to extrinsic (externally motivated) (Teixeira et al., 2021). In the context of eating behaviors, SDT emphasizes that individuals who engage in health-promoting actions due to intrinsic motivations—such as enjoyment or personal satisfaction—tend to exhibit more persistent and positive outcomes (Pelletier et al., 2004). SDT is operationalized through several types of motivational regulation: intrinsic motivation, integrated regulation, identified regulation, introjected regulation, external regulation, and amotivation. Each type reflects varying degrees of autonomy and self-determination in behavior regulation.

Instruments such as the Regulation of Eating Behavior Scale (REBS) capture these dimensions, offering a nuanced view of the motivations behind eating patterns (Pelletier et al., 2004). Research indicates that intrinsic motivation and integrated regulation are positively associated with healthier eating behaviors, as these motivations align with personal values and identity (Achour et al., 2022; Teixeira et al., 2021). Conversely, extrinsic motivation—particularly amotivation and external regulation—is linked to disordered eating behaviors, including binge eating and emotional eating (Feret et al., 2023). Studies also suggest that individuals with introjected regulation may experience internal pressures, such as guilt or shame, leading to restrictive dieting or overeating in response to emotional distress (Akey et al., 2013; Hepworth and Paxton, 2007).

Integrating SDT into dietary intervention programs can foster a deeper understanding of how different motivational drivers contribute to eating habits. For example, interventions promoting intrinsic motivation for healthy eating, such as enjoyment in meal preparation, have shown promise in enhancing long-term adherence to dietary guidelines (Cardoso et al., 2020; Schulte et al., 2018). While SDT offers valuable insights into motivational regulation, it does not address how physical and psychosocial factors, such as body image or cultural norms, interact with motivation to influence eating behaviors.

2.3. Emotional and psychosocial factors

Emotional and psychosocial factors, including stress, body image concerns, and cultural norms, play a significant role in shaping eating behaviors (Emilien and Hollis, 2017; Ljubičić et al., 2023). Emotional eating, characterized by the consumption of food in response to emotional cues rather than hunger, is a well-documented behavior associated with stress and negative affect (Anderson, 2014; Jones et al., 2001).

Emotional eating is prevalent among individuals experiencing high levels of stress or those with negative body image perceptions, as these factors can trigger coping mechanisms that involve food (Irvine et al., 2019; Maloney et al., 1989).

Body image, in particular, has been linked to disordered eating patterns, where individuals with body dissatisfaction may engage in restrictive or binge eating behaviors (Irvine et al., 2019). Research has shown that cultural ideals of thinness and societal pressure contribute to these behaviors, particularly in young adults who face significant peer and media influence (Garfinkel and Newman, 2001; Martinez-Avila et al., 2020). The Eating Attitudes Test (EAT) and the Addiction-Like Eating Behavior Scale are widely used to assess disordered eating patterns and have been validated across different populations (Garner et al., 1982; Legendre and Bégin, 2021). These scales provide insights into how body image, emotional states, and social influences drive maladaptive eating habits, underscoring the importance of addressing these psychosocial factors in dietary interventions.

Psychonutrition is an emerging field that integrates psychological and nutritional perspectives, examining how mental health and dietary behaviors are interconnected (Achour et al., 2022; Schlienger, 2013). Psychonutrition focuses on how emotional well-being influences food choices and how dietary patterns impact mental health outcomes. Studies indicate that improving mental health through therapeutic support and coping strategies can positively influence eating behaviors, particularly in individuals prone to emotional or stress-related eating (Feret et al., 2023; Schlienger, 2013). This integrative approach highlights the need for dietary interventions that address both psychological and physiological aspects, acknowledging that emotional regulation is integral to fostering healthy eating habits.

Although significant progress has been made in understanding the motivational and emotional drivers of eating behaviors, a notable gap remains in identifying specific predictors of control loss in eating patterns. Traditional models like HBM and SDT provide foundational insights into health motivations and behavioral regulation but are limited in their ability to address complex, hierarchical interactions between predictors. Moreover, few studies have applied advanced analytical methods, such as decision tree regression, to map the interrelationships between motivational, physical, and psychosocial variables in eating behavior prediction.

This study seeks to fill this gap by employing decision tree regression to identify hierarchical predictors of control loss in eating behaviors. By integrating motivational and physical variables, this approach offers a structured framework for understanding how different factors interact to influence eating patterns. This methodological innovation addresses the limitations of previous models and provides actionable insights for developing targeted interventions that promote self-regulation and healthier dietary choices.

3. Research methodology

3.1. Participants

The study sample comprised 659 individuals selected via convenience sampling from diverse demographic backgrounds in rural and urban areas of Western Romania. Of these participants, 124 were male (18.82%) and 535 were female (81.18%), illustrating a predominantly female sample. Data collection occurred across various sites in Western Romania, capturing participants from a wide range of socioeconomic backgrounds. This convenience sampling approach was chosen for its practicality and suitability to the study's focus and regional demographic landscape. Participants were recruited through multiple accessible channels such as social media groups, community centers, and local events. These recruitment methods, as noted in previous studies, often tend to attract more female participants, especially in research related to health and dietary behaviors (Rad et al., 2024; Dicu et al., 2024). Consequently, a gender imbalance emerged in the sample; however, the study did not set out to perform gender-specific analyses, and this distribution reflects natural response patterns under the given recruitment conditions.

To ensure ethical integrity, informed consent was obtained from each participant before they engaged in the study. **Table 1** outlines the demographic characteristics of the sample, detailing variables such as gender distribution, residential background, educational attainment, occupational status, and marital status across the urban and rural regions of Western Romania.

In the sample of 659 valid responses, the mean age was calculated at 31.16 years (SD = 11.97), with participants ranging from 18 to 66 years. For the weight category, based on 659 valid responses, the mean was 69.14 kg (SD = 17.02), with weights spanning from 40 to 163 kg. Due to missing data, the income variable was based on 657 responses and averaged RON 3,727.46 (SD = RON 2,500.63), with an income range from RON 0.00 to RON 15,000.00.

Table 1. Decision tree regression model performance.

Splits	Training Sample (n)	Test Sample (n)	Test MSE
116	526	131	0.902
Total 657	526	131	

3.2. Instruments

The study employed two primary validated instruments to assess control loss in eating behaviors and explore the motivational regulations underlying these behaviors, enabling a nuanced understanding of how various motivational factors contribute to eating habits. The first instrument, the General Food Cravings Questionnaire-Trait (GFCQ-T), developed and validated by Nijs et al. (2007), is designed to measure trait-level food cravings. Specifically, we used the loss of control subscale to capture tendencies related to overeating when experiencing cravings. This subscale includes items that reflect a lack of restraint, such as, "If I eat what I crave, I often lose control and eat too much", "When I start eating, I find it hard to stop", and "Once I start eating something I crave, I know I won't be able to stop" (Nijs et al., 2007). This scale's high reliability (Cronbach's Alpha = 0.903) underpins its robustness in measuring control-related aspects of food cravings, making it an ideal instrument for studying self-regulatory challenges in eating behaviors.

The second instrument used in this study, the Regulation of Eating Behavior Scale (REBS), was validated by Pelletier, Dion, Slovinec-D'Angelo, and Reid (2004) and provides a multidimensional measure of motivational regulation in eating behaviors, grounded in the Self-Determination Theory (SDT). This scale comprises several subscales, each capturing a distinct motivational construct that influences how individuals regulate their eating habits.

The Intrinsic Motivation subscale assesses the pleasure and inherent satisfaction derived from eating healthily, with sample items including, "It is fun to create meals that are good for my health" and "I enjoy finding new ways to make healthy meals" (Pelletier et al., 2004). This motivation reflects an internal drive, aligning closely with self-determined behavior. Integrated Regulation represents motivation that is deeply ingrained within an individual's values and identity, encapsulated in items like, "Healthy eating is an integral part of my life" and "Eating healthily aligns with other important aspects of my life" (Pelletier et al., 2004). This form of regulation indicates that healthy eating is a reflection of personal values rather than external pressures.

The Identified Regulation subscale captures the recognition of the benefits of healthy eating as an important and self-endorsed goal. Example items include, "I think it will ultimately help me feel better" and "It's a good thing I can do to feel better overall" (Pelletier et al., 2004). Unlike intrinsic motivation, identified regulation is driven by the value placed on the outcome rather than enjoyment. Introjected Regulation reflects behaviors driven by internal pressures, such as guilt or shame, as seen in items like, "I don't want to feel ashamed of how I look" and "I would feel humiliated if I didn't have control over my eating behavior" (Pelletier et al., 2004). These responses often signify partial internalization of external demands.

The External Regulation subscale measures behaviors driven by external pressures or expectations, with items such as "Close others insist that I do this" and "People around me expect me to do this" (Pelletier et al., 2004). This regulation is externally controlled, where behaviors are performed to meet external demands or avoid negative consequences. Lastly, Amotivation reflects a lack of motivation or perceived purpose in regulating eating behavior, as demonstrated in items like, "I don't really know. I feel like I'm wasting my time trying to regulate my eating behavior" and "I don't see how my efforts contribute to my health" (Pelletier et al., 2004).

Each REBS subscale exhibited strong internal consistency, with Cronbach's Alpha values ranging from 0.82 to 0.93, underscoring their reliability in measuring distinct motivational aspects of eating regulation. The combination of the GFCQ-T and REBS provided a comprehensive framework for examining both motivational and physiological predictors of control loss in eating behaviors, highlighting the role of targeted motivational factors in educational interventions aimed at enhancing self-regulation and promoting healthier eating habits (Nijs et al., 2007; Pelletier et al., 2004).

For assessing preferred food types, we employed a single-item research question that offered participants a straightforward selection between different taste categories, ensuring ease of response and minimizing response burden. The item, presented in English, read: "Do you prefer foods that are: sweet (code 1), salty (code 2), spicy (code 3), fatty (code 4), sour (code 5), combination (code 6)", allowing participants to choose one unique response from the following options: sweet, salty, spicy, fatty, sour, or a combination of flavors. This approach was chosen for its simplicity and clarity, facilitating rapid and intuitive responses. Using a single-item measure for food preference provided direct insight into participants' dominant taste inclinations without the complexity of multi-item scales, which can sometimes lead to cognitive fatigue. This format also aligns with recommendations in food preference research, where single-item questions have been shown to yield reliable responses, particularly for straightforward preferences such as taste types.

In addition to the primary instruments, a single-item research question was included to assess participants' daily meal frequency. The question asked, "How many main meals do you have per day: 1, 2, 3, or more?" Participants were instructed to select only one response that best represented their typical daily meal pattern. This straightforward, single-option question aimed to capture an essential aspect of eating habits by providing a quick and easy means to gauge meal frequency, a factor that can be relevant in understanding overall eating behaviors and patterns of control loss.

4. Results

This section presents the outcomes of the decision tree regression analysis used to identify predictors of control loss in eating behaviors. The analysis included a split dataset, model evaluation metrics, feature importance rankings, and the hierarchical structure of predictor splits in the decision tree. Each aspect of the results is presented in detail below.

The decision tree regression model was developed using a training dataset of 526 observations and tested on a separate dataset of 131 observations. The model aimed to predict control loss in eating behaviors based on various motivational, demographic, and physical factors. **Table 1** summarizes the training and testing sample sizes, along with the test mean squared error (MSE) for the model.

The model was trained on a total of 116 splits, yielding a test MSE of 0.902, which indicates the average squared difference between the predicted and actual values on the test data. This MSE serves as a primary evaluation metric, assessing the accuracy of the model's predictions.

Table 2 presents additional performance metrics for the decision tree model, including the root mean squared error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and R^2.

Table 2. Decision tree regression evaluation metrics.

Metric	Value
MSE	0.902
RMSE	0.95
MAE/MAD	0.722
MAPE	455.32%
R^2	0.092

The model's mean squared error (MSE) of 0.902 reflects the average squared difference between the predicted and actual values, offering a broad measure of the model's accuracy. A closely related metric, the root mean squared error (RMSE) of 0.95, provides a more interpretable measure by presenting this error in the same units as the dependent variable, thus helping to contextualize the accuracy more clearly. The mean absolute error (MAE), calculated at 0.722, highlights the average absolute difference between predictions and actual values, effectively assessing prediction accuracy without disproportionately weighting larger errors. The mean absolute percentage error (MAPE) is notably high at 455.32%, suggesting a considerable degree of variability in the dataset. This high MAPE value likely reflects the complexity and diverse nature of the predictors involved, as well as challenges in consistently predicting control loss in eating behaviors.

Finally, the model's R^2 value of 0.092 indicates that only 9.2% of the variance in control loss behaviors is explained by the predictors used. This low R^2 suggests that additional variables or more complex relationships may be needed to fully account for the factors influencing control loss in eating behaviors. Taken together, these metrics suggest that while the model provides some predictive insight, its accuracy is moderate, and the presence of a high MAPE and low R^2 indicates room for further refinement and exploration of other potential influences.

The relative importance of each predictor variable was calculated to determine which factors contribute most significantly to control loss in eating behaviors. **Table 3** outlines the relative importance scores of each predictor.

Table 3. Feature importance rankings.

Predictor	Relative Importance
Amotivation	25.513
External Regulation	20.203
Introjected Regulation	12.921
Intrinsic Motivation	10.111
Identified Regulation	9.264
Preferred Food	6.430
Integrated Regulation	5.739
Weight	3.387
Age	2.867
Height	1.814
Income	0.760
Marital Status	0.760
Gender	0.128
Meals	0.104

The feature importance analysis provides insights into the relative contribution of each predictor variable to the decision tree model's performance in predicting control loss in eating behaviors. In a decision tree regression model, feature importance scores are derived by evaluating the improvement in the model's performance, typically measured by a reduction in deviance or impurity (such as variance in regression) every time a variable is used to make a split. The more a variable contributes to reducing this error, the higher its importance score.

In this model, the feature importance values are calculated based on the sum of improvements in deviance across all splits involving each predictor variable. This cumulative importance allows us to rank variables by their predictive power and influence on the target variable, control loss in eating behaviors.

The highest-ranked predictor in the model, amotivation (25.513), shows the strongest influence on control loss in eating behaviors. This score suggests that participants who lack motivation to regulate their eating habits are highly susceptible to losing control, aligning with Self-Determination Theory’s concept that low intrinsic motivation can lead to poor self-regulation. From a machine learning perspective, amotivation’s high importance score indicates its consistent ability to reduce model error, frequently creating effective splits in the decision tree.

External regulation (20.203), the second most important feature, captures behaviors influenced by external pressures, such as social expectations. This variable’s importance suggests that individuals who are motivated by external influences are more prone to control loss. The high score for external regulation reflects its substantial contribution to reducing variance within the model, thus strengthening predictive accuracy.

Introjected regulation (12.921), which ranks third, reflects internal pressures like guilt or shame, often leading to impulsive or uncontrolled eating behaviors. The model highlights introjected regulation’s relevance, as it consistently contributes to reducing deviance, creating valuable splits within the tree structure based on these psychological stressors.

While intrinsic motivation (10.111) ranks lower than external regulation, it still plays a significant role. Participants who derive inherent satisfaction from healthy eating are less likely to experience control loss, and splits involving intrinsic motivation moderately reduce error, capturing nuanced motivations behind eating behavior that support the decision tree’s performance.

Identified regulation (9.264), representing motivations tied to personal values (such as health and self-care), has a lower importance score but still indicates that individuals who eat for self-endorsed reasons may display more stable eating patterns. Though weaker than the top predictors, identified regulation aids in reducing error, contributing to the model’s predictive capacity.

The preferred food type (6.430) also plays a moderate role, indicating that specific cravings, like sweet or salty foods, can affect self-regulation. Its score reflects its influence in particular branches, especially when combined with motivational variables, suggesting that preferences might amplify motivational states' effects on control loss.

With a moderate importance score, integrated regulation (5.739) implies that viewing healthy eating as integral to one’s lifestyle slightly impacts control. Though less impactful than other motivations, integrated regulation still aids in error reduction and helps segment participants with identity-linked motivations toward eating behavior.

The physical characteristics of weight (3.387) and age (2.867) have lower importance scores, yet they still contribute to the model by capturing demographic variability. These variables provide secondary splits, refining predictions within demographic segments and suggesting interactions between physical factors and motivational drivers. Height (1.814) has minimal influence on control loss, indicating it is not a significant predictor in this context. However, it may support minor branches by offering slight error reduction, assisting in demographic segmentation.

Income and marital status (both 0.760) have very low importance, indicating limited predictive power for control loss. These variables are likely included due to weak interactions with more impactful features rather than independent predictive strength.

Lastly, gender (0.128) and meal frequency (0.104) exhibit the lowest importance scores, suggesting they have minimal influence on the model's predictions and seldom feature in tree splits. This low importance reflects that control loss in eating behaviors is driven more by motivational factors than by demographic characteristics like gender or basic meal frequency. Together, these feature importance scores highlight the dominant role of motivational factors, while demographic and physical characteristics contribute minimally in this model.

In decision trees, feature importance is typically derived through methods such as Gini importance or mean decrease in impurity, which evaluate how much each feature reduces the impurity in each split. Impurity is often measured by variance in regression tasks, and each split's reduction in impurity is aggregated for each feature. High importance scores indicate that a feature consistently provides informative splits across multiple nodes, aiding in reducing the overall prediction error.

In this model, motivational factors like amotivation and external regulation frequently appear in splits, contributing significantly to reducing variance in predictions. These variables capture the most impactful pathways within the tree, providing reliable information that improves the accuracy of predictions. In contrast, demographic factors with lower importance scores offer minimal variance reduction, suggesting they add little predictive value and primarily serve as secondary or tertiary split criteria.

The dominance of motivational variables aligns with findings from behavioral psychology, which indicate that intrinsic and extrinsic motivations are critical in understanding eating behaviors. From a machine learning standpoint, the clear hierarchical pattern of feature importance supports the model's robustness in isolating key predictors, while lower-scoring variables may be refined or excluded in future models to enhance predictive efficiency.

The decision tree model's hierarchical structure is based on a series of splits, each designed to optimize the predictive power of subsequent branches. **Table 4** provides the key splits, detailing the number of observations in each split, the split points for each predictor, and the improvement in model deviance at each split.

Table 4. Splits in tree.

	Obs. in Split	Split Point	Improvement
Amotivation	526	0.328	0.117
External regulation	341	2.256	0.090
External regulation	334	−0.537	0.047
Preferred food	206	−0.529	0.065
Introjected regulation	64	−0.907	0.107
Intrinsic motivation	128	0.582	0.112
Introjected regulation	69	0.589	0.095
Introjected regulation	185	−0.741	0.067

Table 4. (*Continued*).

	Obs. in Split	Split Point	Improvement
Intrinsic motivation	30	−1.265	0.331
Identified regulation	155	−1.502	0.057
Preferred food	145	1.606	0.065
Integrated regulation	130	0.697	0.055
Introjected regulation	113	1.421	0.073
External regulation	103	0.067	0.061
Age	22	0.485	0.384

Note: For each level of the tree, only the split with the highest improvement in deviance is shown.

The decision tree model for predicting control loss in eating behaviors reveals key splits that maximize predictive accuracy by systematically reducing model deviance at each branching point. The initial and most significant split occurs on the variable amotivation, with a threshold of 0.328, yielding an improvement in model deviance of 0.117 across all 526 observations in the training set. This large reduction highlights amotivation as the most influential predictor, suggesting that individuals with higher levels of amotivation are particularly susceptible to experiencing control loss in their eating behaviors. Following this, external regulation emerges as the second critical predictor, with a split at 2.256, reducing deviance by 0.090. This split reflects the model's recognition that participants influenced by external pressures are also prone to difficulties in self-regulation.

As the tree progresses, introjected regulation and intrinsic motivation further refine the branches. For example, introjected regulation creates additional splits at -0.907 and 0.589, with improvements of 0.107 and 0.095, respectively. These splits emphasize the impact of internal pressures, such as guilt or shame, on eating behaviors. Similarly, intrinsic motivation splits at 0.582 and −1.265, with respective deviance reductions of 0.112 and 0.331, indicate that a genuine enjoyment of healthy eating may mitigate control loss.

Interestingly, as the tree extends to deeper levels, certain physical variables, such as age, begin to make notable splits. For instance, a split in age at 0.485 contributes an improvement of 0.384 in deviance, though its impact remains comparatively minor in the overall model. The dominance of motivational factors, particularly amotivation, external regulation, and introjected regulation, underscores their central role in predicting control loss, while physical characteristics serve to fine-tune predictions within specific demographic segments. These findings highlight how the decision tree model prioritizes psychological drivers over demographic factors, enhancing our understanding of the pathway contributing to self-regulation challenges in eating behaviors.

Figure 1 presents the predictive performance of the decision tree regression model, comparing the observed test values on the x-axis with the predicted test values on the y-axis. The diagonal red line represents the ideal scenario where predicted values perfectly match observed values. Points lying along this line indicate accurate predictions, while points further away signify larger prediction errors.

In this plot, a clustering of points around the horizontal middle range shows that the model generally provides reasonable predictions close to zero. However, the scatter of points around the line and the absence of a tight clustering around the red line indicate variability in prediction accuracy. This dispersion suggests that while the model captures some patterns in the data, its ability to predict extreme values is limited, likely due to the complexity and variability within the dataset. The deviation of points from the red line highlights the moderate predictive performance of the model, which aligns with the model's relatively low R^2 value and high MAPE discussed earlier.

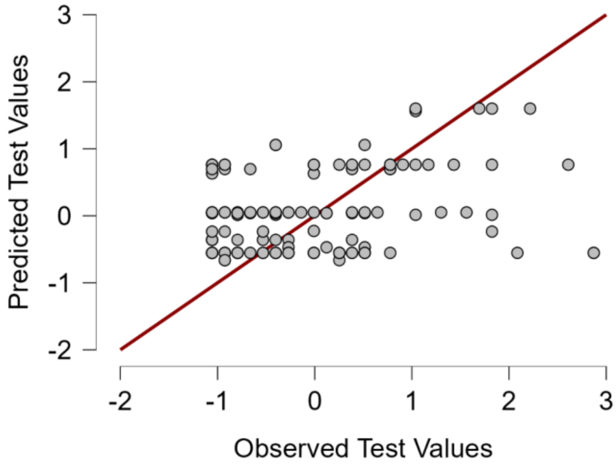

Figure 1. Predictive performance plot.

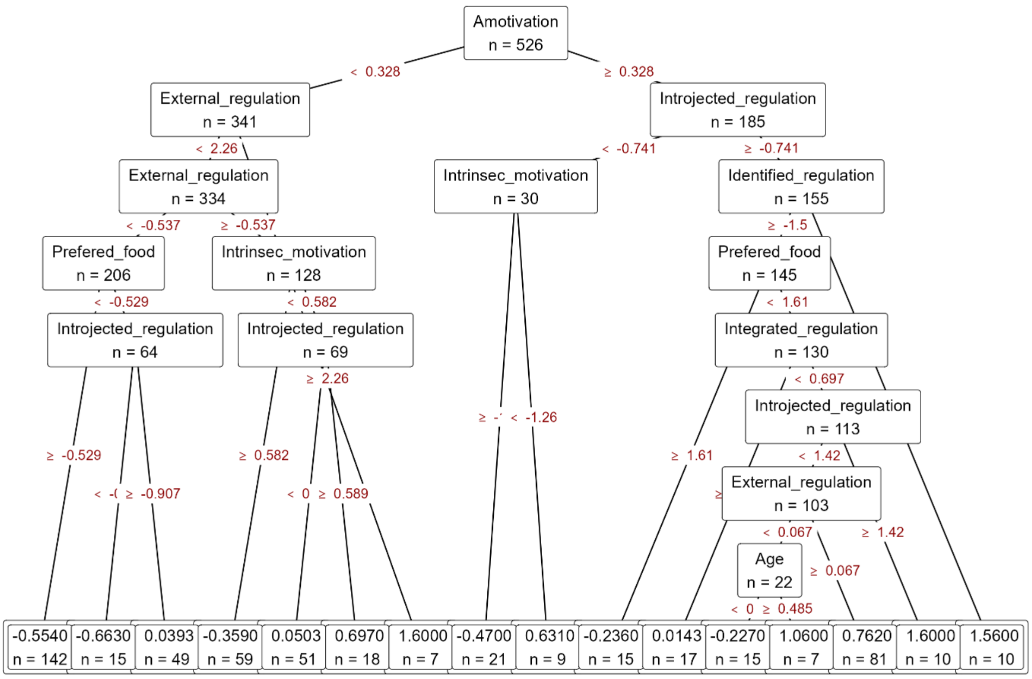

Figure 2. Decision tree plot.

Figure 2 displays the decision tree model developed to predict control loss in eating behaviors, illustrating the hierarchical structure of predictor variables and the splits at each node. The model begins with the root node, which splits based on amotivation at a threshold of 0.328, dividing the sample of 526 observations into two branches. This initial split highlights amotivation as the most influential predictor, suggesting that individuals with amotivation levels above 0.328 are more likely to experience control loss in their eating behaviors.

As we move down the tree, subsequent splits occur based on other motivational factors, such as external regulation, introjected regulation, and intrinsic motivation. The tree structure indicates that external regulation appears frequently, particularly in the left branch, with splits at various thresholds (e.g., 2.256, −0.537), emphasizing its strong predictive power in differentiating control loss levels among participants influenced by external pressures. Similarly, introjected regulation creates multiple branches, highlighting its role in capturing internal pressures, such as guilt or shame, that might impact self-regulation.

Intrinsic motivation and identified regulation appear in branches at different levels, indicating their moderate impact on predicting control loss. For example, a split on intrinsic motivation at 0.582 and another at −1.26 suggest that individuals with higher intrinsic motivation may experience better control over eating behaviors. Identified regulation, which appears in the right branch, also plays a role, with a split at −1.5 that contributes to refining predictions in specific subgroups.

Additional predictors, such as preferred food type and age, appear in deeper branches of the tree, showing their secondary role in the model. For instance, preferred food splits at −0.529 and 1.61, indicating that specific food preferences may interact with motivational factors to influence control loss. Age appears toward the bottom of the tree with a split at 0.485, highlighting that while age contributes to the model, its impact is minimal compared to the primary motivational factors.

Each terminal node at the bottom of the tree represents a predicted value for control loss in eating behaviors, with values calculated based on the mean response of observations in that group. The variety of pathways through the tree reflects the complexity of interactions among motivational, demographic, and preference-based factors. Overall, the decision tree plot demonstrates that motivational variables play a dominant role in predicting control loss, with amotivation, external regulation, and introjected regulation driving the primary structure of the model.

5. Discussions

This study sought to identify and understand the motivational and physical predictors of control loss in eating behaviors through decision tree regression analysis. The findings indicate that motivational factors, particularly amotivation, external regulation, and introjected regulation, are the primary predictors of control loss. This section interprets the results in the context of existing literature, discusses implications, addresses limitations, and suggests future research directions.

The prominence of amotivation and external regulation in predicting control loss aligns with previous research underscoring the role of psychological and motivational factors in eating behaviors (Pelletier et al., 2004; Verzijl et al., 2018). Amotivation, or a lack of intrinsic motivation, has been associated with difficulty in regulating eating behaviors and is likely a central contributor to overeating or binge episodes, as individuals may lack personal reasons to engage in self-control (Stapleton et al., 2016).

External regulation, on the other hand, reflects behaviors driven by external pressures or societal expectations, which often undermine personal autonomy and lead to less stable, externally motivated eating patterns (Waters et al., 2001). This finding resonates with Self-Determination Theory, which posits that individuals motivated by external factors are less likely to sustain behavior change due to the lack of internalization of the behavior’s benefits (Dalton et al., 2013).

Our findings align closely with the seminal work of Pelletier et al. (2004), which underscores the central role of amotivation in eating behaviors. The observed association between low intrinsic motivation and control loss in eating habits validates the critical influence of amotivation, a finding that has significant implications for developing interventions targeting internal regulatory mechanisms. Similarly, the importance of external regulation in our model corroborates the research by Dalton et al. (2013), which highlights the destabilizing effects of external pressures, such as societal expectations and peer influences, on eating behavior.

Interestingly, our findings diverge from the conclusions drawn by Kininmonth et al. (2021), where physical factors like body weight and age were found to significantly influence eating behaviors. In contrast, our study suggests that motivational constructs, particularly the balance between intrinsic and extrinsic motivators, are more salient predictors of control loss in our population. This discrepancy may reflect differences in sample demographics or methodological approaches, and it highlights the need for future comparative studies to explore these variances. By employing decision tree regression, this study expands upon the existing literature by introducing a hierarchical perspective on how motivational and emotional constructs interact. This approach not only clarifies the layered relationships between intrinsic and extrinsic motivators but also provides a novel framework for understanding the complexity of eating behaviors. The hierarchical structure revealed by our model emphasizes that interventions must address these motivational layers comprehensively rather than treating them as isolated factors.

The importance of introjected regulation, which involves internal pressures such as guilt or shame, highlights the impact of psychological stressors on eating behaviors. Introjected regulation can lead to impulsive eating as individuals attempt to alleviate uncomfortable emotions, a pattern that has been observed in populations struggling with eating disorders (Van Vuuren et al., 2018； Waters et al., 2001). This aligns with the Behavioral Susceptibility Theory, which suggests that some individuals have heightened susceptibility to external and internal cues that influence appetite and satiety (Carnell and Wardle, 2008; Llewellyn and Fildes, 2017). The presence of these motivational factors in the decision tree model suggests that individuals’ regulation of eating behavior is significantly influenced by their psychological and emotional responses to food.

The relatively minor roles of physical characteristics, such as weight and age, in the model indicate that demographic factors may not be as impactful as motivational variables in predicting control loss in eating behaviors. This is consistent with findings by Kininmonth et al. (2021), which emphasize that appetite regulation and emotional factors are often more predictive of eating behaviors than physical characteristics alone. The secondary influence of physical variables suggests that while they may contribute to individual differences in eating behavior, the motivational and emotional dimensions are more central to understanding control loss.

The study's findings offer important implications for interventions targeting eating behaviors, particularly in educational and therapeutic settings. Given the significant influence of amotivation, external regulation, and introjected regulation, programs aimed at fostering healthier eating habits should emphasize enhancing intrinsic motivation and reducing reliance on external pressures. Interventions could integrate cognitive-behavioral strategies to help individuals identify and challenge external and introjected motivations, potentially replacing them with more autonomous and self-endorsed reasons for healthy eating (Stapleton et al., 2016). Teaching self-regulation techniques, such as mindful eating and emotional awareness, could further help individuals recognize and manage emotional triggers associated with control loss (Verzijl et al., 2018). Additionally, health education programs should incorporate discussions around the impact of social and cultural pressures on eating behaviors, encouraging participants to cultivate a personal, internally driven approach to food choices.

While this study provides valuable insights, several limitations must be acknowledged. First, the decision tree regression model, while effective at capturing hierarchical relationships, may oversimplify the complex interactions among predictors compared to other machine learning approaches like random forests. The moderate predictive accuracy, as reflected in the R^2 and MAPE values, suggests that additional variables not included in this study may influence control loss in eating behaviors. Second, the use of convenience sampling limits the generalizability of the findings to a broader population, as the sample may not fully capture diverse socioeconomic and cultural backgrounds that could influence eating behavior (Kininmonth et al., 2020). Finally, the cross-sectional nature of the data restricts causal inference, meaning that the observed associations should not be interpreted as definitive causal relationships.

Future research should explore additional psychological and contextual variables, such as stress, socioeconomic status, and body image, to improve model accuracy and provide a more comprehensive understanding of control loss in eating behaviors. Expanding the model to include environmental factors and examining potential interactions among predictors could yield a more nuanced perspective. Additionally, longitudinal studies are needed to track changes in motivational factors and eating behavior control over time, which could help establish causal pathways. Investigating other machine learning models, such as random forests or gradient boosting, could further enhance predictive performance and offer deeper insights into complex predictor relationships (Kininmonth et al., 2021; Vandyousefi et al., 2022). Finally, replicating this study across different cultural contexts would be beneficial to validate the model's applicability and strengthen its external validity, especially given that appetite and eating behaviors can vary significantly across populations (Carnell and Wardle, 2008; Llewellyn and Fildes, 2017).

Moreover, integrating supervisory frameworks and training tools into research on eating behavior modeling could offer unique insights into the application of psychological theories in education and practice. For instance, the supervision session pyramid, as presented by Watkins Jr et al. (2020), may provide a structured framework for mentoring researchers in interdisciplinary contexts. Addressing roadblocks and recommending remedies, as highlighted in psychotherapy supervision literature (Watkins Jr et al., 2021), can further refine methodological approaches. Additionally, managing problematic self-efficacy inferences in novice researchers could be informed by strategies detailed by Watkins Jr et al. (2022). Process-based psychological theories, as applied in the Romanian educational context (Cădariu and Rad, 2023), could guide future studies in understanding motivational aspects related to eating behaviors and their broader implications.

6. Conclusions

The primary aim of this study was to identify the motivational and physical predictors of control loss in eating behaviors using a decision tree regression model. The research question guiding this inquiry was: What are the motivational and physical predictors of control loss in eating behaviors as identified through decision tree regression, and how can these findings inform educational interventions aimed at enhancing self-regulation and promoting healthier eating patterns? Based on the results, several key conclusions can be drawn.

First, the findings reveal that motivational factors, particularly amotivation, external regulation, and introjected regulation, are the strongest predictors of control loss in eating behaviors. These variables were consistently prioritized in the decision tree model, indicating that individuals with high levels of amotivation or driven by external pressures are more susceptible to losing control over their eating habits. This aligns with Self-Determination Theory, which suggests that low intrinsic motivation and high external influences undermine self-regulation (Pelletier et al., 2004). These insights emphasize the need for interventions that focus on reducing amotivation and external pressures while fostering intrinsic motivation to promote better eating self-control.

Second, while physical and demographic factors such as age and weight were included in the model, their influence was comparatively minor. These factors only appeared in deeper levels of the decision tree, suggesting that they contribute to predicting control loss in specific contexts or subgroups but do not play a central role. This outcome underscores that motivational dimensions, rather than physical attributes, are more critical in determining control loss in eating behaviors. As such, interventions may be more effective if they prioritize motivational factors over demographic characteristics.

Third, the model's moderate predictive accuracy, as evidenced by the MSE and R^2 values, indicates that while the selected predictors offer some insight into control loss, other unexamined factors may also play a role. The relatively high mean absolute percentage error (MAPE) suggests variability in the dataset, highlighting the complexity of eating behaviors. Future research may benefit from incorporating additional psychological or environmental variables to enhance the predictive power of models addressing eating behavior control.

In alignment with the research question, the findings suggest that educational interventions targeting eating behaviors should focus on enhancing intrinsic motivation and reducing reliance on external regulation. Programs could emphasize the development of personal motivation, self-regulation strategies, and emotional resilience to better equip individuals to manage their eating behaviors. Addressing the psychological dimensions of eating, rather than solely focusing on dietary prescriptions, may offer a more effective pathway for fostering long-term behavior change and promoting healthier eating patterns. Given that amotivation and external regulation were primary predictors of control loss, educational programs should focus on strategies to reduce amotivation and external pressure while fostering intrinsic motivation. Interventions could incorporate modules on self-reflection, personal goal-setting, and internalization of healthy eating habits, encouraging individuals to find personal value in their dietary choices. Additionally, teaching self-regulation skills and coping mechanisms for managing social and emotional triggers may support more resilient eating behaviors. Integrating these motivational strategies into health and nutrition education may yield more sustainable outcomes by addressing the psychological roots of eating behaviors.

This study has several limitations. First, the decision tree model, while useful for identifying hierarchical relationships, has limited capacity to capture complex interactions between predictors compared to other machine learning algorithms. While the decision tree regression model provides novel insights into hierarchical predictors, its moderate predictive accuracy suggests potential unexplored variables.

Furthermore, the use of convenience sampling limits the generalizability of the findings to broader populations, as the sample may not fully represent diverse demographic groups. Lastly, the cross-sectional nature of the data restricts causal interpretations, as observed relationships may not accurately reflect dynamic changes in eating behaviors over time.

Future research should consider expanding the range of predictors included in models of eating behavior control. Incorporating additional psychological variables, such as stress, body image perception, and emotional eating tendencies, could enhance the model's predictive power (Marici et al., 2024). Longitudinal studies are recommended to better understand how motivational factors and control loss in eating behaviors evolve over time. Exploring other machine learning approaches, such as random forests or gradient boosting, may also provide more nuanced insights into predictor interactions. Additionally, replicating this study in diverse populations would strengthen the external validity of the findings, facilitating the development of more inclusive and effective educational interventions for promoting healthier eating behaviors across various demographic groups.

The insights provided by this model have significant practical implications for educators and psychologists. By identifying the hierarchical relationships among personality traits, self-regulation, and eating behaviors, the findings highlight actionable strategies for intervention. Similarly, psychologists working with individuals struggling with disordered eating or emotional eating can use these findings to design targeted interventions that address specific personality traits linked to control loss. For example, individuals with low emotional stability may benefit from therapeutic strategies focused on building resilience and emotional regulation, while those scoring low on conscientiousness might respond well to structured goal-setting frameworks. By applying these targeted strategies, educators and psychologists can enhance self-regulation and reduce the likelihood of control loss in eating behaviors, leading to more sustainable health outcomes.

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