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Florida Agency for Persons with Disabilities

iBudget Algorithm Study

November 7, 2025

iBudget Algorithm Study – Final Report

Table of Contents

Table of Figures

Table of Tables

Table of Equations

Acronyms

Acronym	Definition
AHCA	Agency for Health Care Administration
AIM	Algorithm Implementation Meeting
APD	Agency for Persons with Disabilities
CDMS	Case and Document Management System
CMS	Centers for Medicare and Medicaid Services
DMS	Florida Department of Management Services
FAC	Florida Administrative Code
FS	Florida Statute
FY	Fiscal Year
HB	House Bill
HCBS	Home and Community-Based Services
IDD	Intellectual and Developmental Disabilities
MI	Mutual Information
PDP	Partial Dependence Plots
SAN	Significant Additional Needs
SHAP	SHapley Additive exPlanations Values
RMSE	Root Mean Squared Error
QSI	Questionnaire for Situational Information
WSC	Waiver Support Coordinator

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ISF also extends appreciation to the Florida Department of Management Services (DMS), including the Florida Digital Services Deputy Chief Data Officer, DMS Secretary, and the DMS Data Team, for their collaboration, thoughtful feedback, and technical guidance throughout the development and review process of the iBudget Algorithm Study. Their partnership helped ensure alignment with statewide data, system, and policy standards. The State of Florida's dedication to the betterment of the provision of services for the IDD community across the state is commendable. The investment of funding, support of system advancements, and direction to conduct the study presented in this report demonstrate Florida's commitment to ensuring all Floridians, including those with disabilities, live healthy, safe, and fulfilling lives in their communities.

1 Purpose

The HCBS iBudget system is a component of Florida's Medicaid waiver program that enables individuals with developmental disabilities to receive personalized care and support within their homes and communities. Central to this system, known as iBudget, is an algorithm that determines each person's individualized budget based on key factors such as age, living setting, and information from the Questionnaire for Situational Information (QSI), supplemented by additional assessments when needed. Administered by the Florida Agency for Persons with Disabilities (APD), the iBudget system currently supports more than 36,000 individuals, with an additional 19,000 individuals on the pre-enrollment list.

Florida House Bill 1103 (CS/CS/HB 1103), signed into law on June 10, 2025, introduces significant reforms aimed at enhancing services for individuals with developmental disabilities in Florida. A component of this legislation was the requirement for APD to contract for a comprehensive study of the iBudget allocation algorithm, with particular emphasis on ensuring compliance with person-centered planning requirements under section 393.0662, Florida Statutes (FS). The scope of the study included reviewing, evaluating, and identifying recommendations regarding the algorithm used to determine the amount of funding each iBudget enrollee receives.

The iBudget system, established in 2010, was designed to provide individuals with greater flexibility and control over their services by allocating funding based on a standardized algorithm. The intent of the iBudget system is to ensure the equitable distribution of resources among individuals with similar needs.

In response to HB 1103, the iBudget Algorithm Study facilitated the assessment of whether the current methodology effectively ensures the equitable allocation of available funds and accurately reflects the level of need for services. Additionally, the study explored potential improvements or alternatives to the existing algorithm to better meet the needs of individuals with developmental disabilities. A report of the findings and recommendations of the study, this document, is required to be submitted to the Governor and Florida Legislature by November 15, 2025, per HB 1103.

The study aligned with broader policy trends emphasizing individualized budgeting and person-centered care, which focused on tailoring resources and supports to the unique preferences, priorities, and circumstances of each individual.

2 Overview

To meet the legislative requirement in HB 1103, an analysis was conducted on the current APD iBudget waiver algorithm. The current algorithm, Model 5b, was developed by professors Tao and Niu in 2015 under the auspices of Florida State University using fiscal year (FY) 2013–14 expenditure data. It provided a strong foundation for individualized budget allocations and achieved a high level of predictive accuracy at the time. However, as service delivery models, provider rates, participant needs, and technology have evolved, the model's performance naturally shifted when tested against recent data.

Following the evaluation of the current algorithm, an assessment of ten alternative algorithm models was conducted. This included approaches ranging from enhanced linear regression methods that maintained interpretability while improving robustness, to sophisticated techniques that could capture complex relationships between individual characteristics and support needs. Three of the models (7, 8, and 10) were excluded as they did not produce single budget allocations as required in section 393.0662(1), FS, for iBudget clients. displays the seven models evaluated.

Figure 1: Alternative Models

Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 9
Re-estimated Linear Regression	Generalized Linear Model with Gamma Distribution	Robust Linear Regression	Weighted Least Squares	Ridge Regression	Log-Normal Regression	Random Forest

It was determined that Model 9, Random Forest, performs best among the evaluated alternative algorithms, and better than the current Model 5b. Accordingly, the recommendation is that Model 9, Random Forest, should be considered for implementation moving forward. provides an overview of the improvement in Model 9 compared to Model 1 (Model 5b re-estimated with current data, new features, and with all data included).

Figure 2: Model 9 Improvement

	Difference Between Model 1 (Model 5b Re-evaluation) and Model 9
Variance Between Claims and Budget Amount	Improved 33%
Error Magnitude	Substantial Reduction
Outliers	0% Outliers – Strengthen Validity

Model 9 outperformed the current model by achieving improved accuracy, reduced magnitude of error related to expenditures (i.e., dollar amount), and is feasible to implement. It is estimated that implementing Model 9 would require a 15.9% statewide funding increase for the provision of client services and cost about $500,000 for technical implementation and ownership over three years. This cost does not include required programmatic changes, such as updating all documentation and stakeholder communication.

This algorithm's role extends beyond mere budget calculations as it fundamentally shapes how resources are distributed, governing the services and levels of care individuals can access, and how person-centered planning principles are implemented in practice.[1] Therefore, this analysis emphasizes phased deployment with comprehensive validation and monitoring to ensure that algorithmic improvements translate into meaningful improvements in service delivery and individual outcomes. This approach recognizes that algorithmic change in disability services can carry profound implications for individual well-being and requires careful attention to unintended consequences and implementation challenges. However, it is important to note that algorithms generate generalized predictions from historical data. Some level of variation or error is inherent and should be expected in all predictive models.

Additionally, the iBudget waiver currently offers a comprehensive range of services designed to meet the diverse needs of participants. As the program evolves, opportunities may arise to enhance or refine the existing service array. Any proposed additions or modifications should be supported by in-depth research to assess alignment with current offerings, estimate utilization and true service costs, and determine potential funding implications. Implementation would also require federal approval, as well as updates to administrative rules, the iBudget handbook, staff training, and public education materials, in addition to technical implementation activities.

[1] Person-centered planning emphasizes the individual's preferences, needs, and goals, ensuring that services and supports are tailored to the person rather than the system. Person-Centered Service Planning in HCBS: Requirements and Best Practices

3 Background

APD supports individuals with disabilities and their families in living, learning, and working within their communities by creating multiple pathways to possibilities. APD provides a variety of social, medical, behavioral, residential, and therapeutic services to Floridians with developmental disabilities. The eligibility criteria are identified in Florida Statutes and rules and include Floridians who are diagnosed with severe forms of autism, cerebral palsy, spina bifida, intellectual disabilities, Down syndrome, Prader-Willi syndrome, and Phelan-McDermid syndrome. Individuals eligible for APD services must be domiciled in Florida, be at least three years old, and have a diagnosed developmental disability that occurred before the age of 18.

The United States Centers for Medicare & Medicaid Services' (CMS) HCBS Medicaid waiver allows the federal government to waive rules that typically apply to Medicaid programs. The use of the HCBS waiver provides states with the opportunity to achieve specific goals and offer services that would not typically be covered by Medicaid. The Florida Agency for Health Care Administration, the state's primary Medicaid administering agency, partners with APD to provide the HCBS waiver program to APD's service population.

The HCBS Medicaid waiver is administered by APD through the iBudget system, enabling APD clients to receive medically necessary support and services that facilitate living in the community. The iBudget system offers a variety of social, medical, behavioral, therapeutic, and residential services to individuals with developmental disabilities. As of 2025, there are more than 36,000 individuals enrolled in the program, with a pre-enrollment list of more than 19,000 people. Each client's iBudget amount is calculated using the allocation algorithm in Rule 65G-4.0214, Florida Administrative Code (FAC), based on age, living setting, and QSI factors, plus any significant additional needs (SAN) identified in individual reviews. These calculations are currently completed in APD's Client Data Management System (CDMS), iConnect, by using the EZ iBudget Calculator. Thus, any changes to the algorithm will take engagement with APD's CDMS vendor, WellSky, which historically has taken multiple months to implement desired system changes for the algorithm and calculator. The SAN process is initiated by an iBudget client following the receipt of their original allocation derived from the algorithm when that amount does not appear to meet their individual needs.

Table 1: iBudget Waiver Process Activities outlines the key steps and roles involved in assessing needs, allocating budgets, and delivering services under Florida's iBudget Waiver. It shows how clients, waiver support coordinators (WSC), service providers, and APD interact from eligibility through claims submission.

During the 2025 legislative session, the Florida Legislature passed HB 1103, which was subsequently signed into law on June 10, 2025. This legislation required APD to contract for a study to review, evaluate, and identify recommendations regarding the algorithm required under section 393.0662, FS, the iBudget implementing statute.

In response to HB 1103, APD engaged ISF, Inc., a Florida and Texas-based consulting firm with the credentials required in HB 1103, to conduct the iBudget Algorithm Study. The study involved research activities to support the development of recommendations to ensure the up-to-date and accurate allocation of resources to Florida's most vulnerable citizens, aligning with both statutory requirements and principles of person-centered care.

Table 1: iBudget Waiver Process Activities

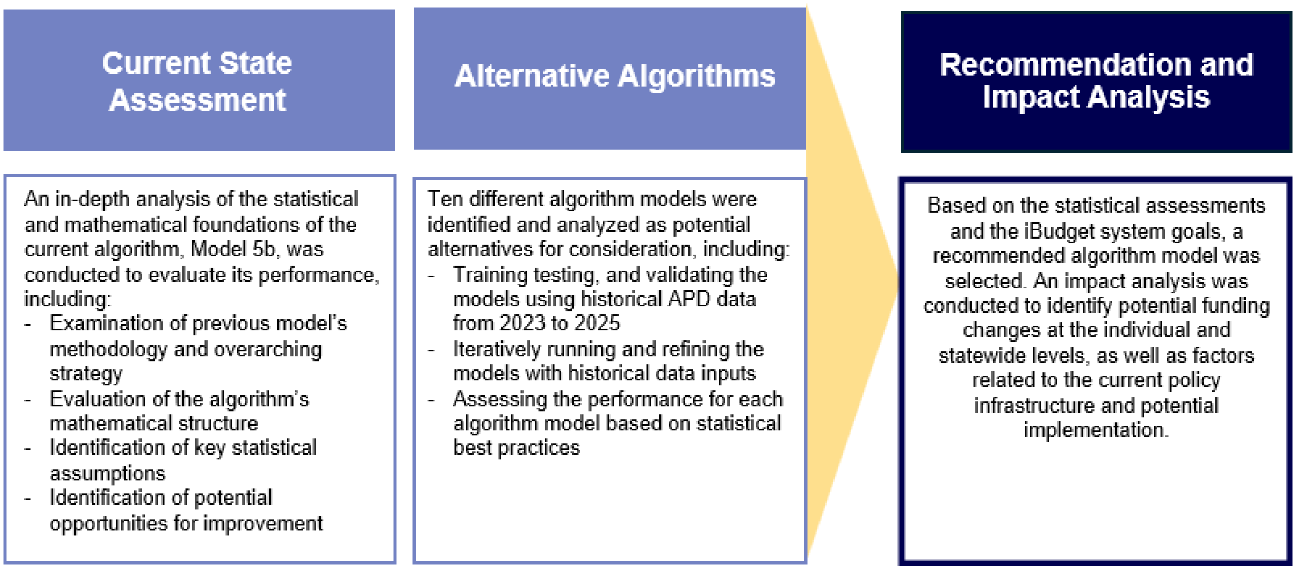
Step	Process Name	Responsible Party	Description / Key Activities*	System(s) Involved	Output*
1.0	Confirm Eligibility	APD	Verify that the client meets eligibility criteria and is enrolled in the iBudget waiver program.	N/A	Confirmed eligibility and enrollment record
1.1	Complete QSI	APD and Client	Conduct an assessment to gather information about client's needs, abilities, and living situation.	iConnect	Completed QSI
1.2	Enrollment	APD	APD completes the enrollment process.	iConnect	Completed enrollment
1.3	Run iBudget Algorithm	APD	Use QSI data, age, and living setting to run the algorithm to calculate the individual budget amount.	iBudget System	iBudget allocation
1.4	iBudget Issued	APD	Release official iBudget allocation for the client.	iConnect	Budget notification
1.5	Initial Cost Plan Developed	APD or WSC	APD or the WSC develops the initial cost plan for the client.	iConnect	Cost plan
1.6	Complete Algorithm Implementation Meeting (AIM) Meeting and Submit Worksheet	WSC and Client	Identify and document client service needs and goals for inclusion in cost plan in AIM Worksheet. This must be submitted within 30 days.	iConnect	Documented service needs
1.7	Issue Notice of iBudget Amount	APD	The notice communicates that the automatic award of algorithm amount if the AIM is not submitted within 30 days.	iConnect	Notice of iBudget Amount
1.8	Create Working Cost Plan Identified in AIM	WSC	Create a cost plan within the individual budget to meet client needs in AIM.	iConnect	Draft working cost plan
1.9	Review/Approve Cost Plan	APD	Review and approve cost plan to ensure alignment with policies, budget, and client needs, including medical necessity.	iConnect	Approved cost plan
1.10	Issue Service Authorization	APD	Generate and issue authorization for approved services to providers.	iConnect	Service authorization
1.11	Deliver Approved Service	Service Provider and Client	Deliver approved services to the client as outlined in the service authorization.	Provider systems	Service delivered
1.12	Submit Claims	Service Provider	Submit claims for payment for delivered services.	Provider billing system / Medicaid	Submitted claims
1.13	Complete and Submit a SAN	WSC and Client	If additional needs exist beyond the budget, complete a supplemental needs assessment for APD review.	iConnect	SAN
1.14	Review SAN Request	APD	Review SAN and determine if additional funding is approved, partially approved, or denied.	EZ iBudget Calculator	Approved SAN
1.15	Update Cost Plan with Additional Needs	WSC	Cost plan is updated by the WCS with additional needs identified in the SANs process	iConnect	Working cost plan

*All documents that require translation for client communication are sent to APD's contracted translation service.

4 Methodology

The methodology supporting the iBudget Algorithm Study was conducted in three primary stages, as demonstrated in Figure 3: iBudget Algorithm Study Methodology.

Figure 3: iBudget Algorithm Study Methodology



The development of the recommended algorithm was guided by rigorous statistical validation and incorporated input from participants and stakeholders to provide a foundation for meaningful improvements. Throughout this process, key assumptions regarding data quality, representativeness, predictor relevance, and population diversity were carefully considered to ensure that the algorithm provides reliable, actionable insights across Florida's communities. The full mathematical analysis for all components of the iBudget Algorithm Study is provided via the link in the Appendix Section 11.1 Scientific Report.

4.1 Assessment of the Current iBudget Algorithm

An in-depth analysis of the statistical and mathematical foundations of Model 5b, the current algorithm used by APD, was conducted following a comprehensive review of the iBudget system documentation, including the QSI. This analysis included the following activities:

- Evaluation of the algorithm's mathematical structure against established best practices in modern data science
- Identification of key statistical assumptions, such as data distribution, error terms, variance, documenting the defined independent and dependent variables, transformation techniques, and model selection strategies
- Identification of potential opportunities for improvement, including opportunities to leverage new technologies and state-of-the-art data analysis techniques

- Examination of the methodology used to establish the statistical framework included an assessment of the rationale behind the inclusion and exclusion of independent variables, the algorithm's approach to outlier management, and the overarching strategy adopted by APD

Following the initial analysis of the algorithm, Model 5b was applied in a secure environment to enable algorithm validation. The Python implementation, which mimics the application of the algorithm, as currently used by APD, reproduces the exact coefficient structure of Model 5b, ensuring mathematical fidelity to the original methodology. All regression coefficients, interaction terms, and transformation procedures match the specifications of the algorithm, enabling direct comparison with the original statistical analysis.

Upon successful validation of how the algorithm runs with mock data, the model was then tested using real historical data provided by APD, including actual allocations made through the iBudget system. Once the data was cleansed and validated, it was fed into the model, and the resulting predictions were compared against actual allocations. This comparison enabled the calculation of error rates and the assessment of the model's average accuracy and reliability, following best practices in statistical model evaluation. As a part of the testing process, the algorithm was then tested in areas beyond performance, including sensitivity to coefficient changes, tolerance to changes in policy, and differences across distinct population subgroups.

4.2 Identification of Alternative Algorithms

To determine which predictors to train, test, and validate the models on, a feature selection analysis was conducted encompassing six FYs of data (September 1, 2019– August 31, 2025, specifically to account for normal billing cycles). Information-theoretic measures, statistical association diagnostics, and multicollinearity controls were applied to identify the optimal set of predictors to use for model development.

After determining the optimal feature set, real historical data was run through 10 alternative algorithms to evaluate their outputs, facilitating an assessment of accuracy, reliability, and other requirements. The outputs were then fully assessed to determine the impact and feasibility of each algorithm, which supported the recommendation of an algorithm model. Models 1-6 present variations of linear regression algorithms, as required in HB 1103, with varying inputs, weights, and formulas. Three of the models (7, 8, and 10) were excluded as they did not produce single budget allocations as statutorily required for iBudget clients. Model 9 demonstrates a different statistical approach for consideration, ensemble, decision-tree-based machine learning.

The alternative algorithms were trained, tested, and validated using data from APD's database, spanning fiscal years 2023-2025. For this analysis, each FY spanned September 1 through August 31 based on how payments were made. Every client record was considered individually whenever an allocation was received (i.e., client year).

4.3 Recommendation of Algorithm and Impact Analysis

After developing and refining alternative algorithms, their performance was evaluated against the objectives of the iBudget system and APD's HCBS program. Multiple iterations were conducted using actual APD data, and the final recommendation for the model(s) was based on their demonstrated performance and alignment with program goals.

To determine the most appropriate algorithmic model to recommend, performance was compared to the baseline performance of Model 1, which has the same computational structure and mathematical formulation as the currently used Model 5b with updated data, including new predictors and all available data (including outliers). This methodology was adopted as Model 5b was not updated after its initial development in 2015. Model 1 allows for an assessment of how Model 5b's algorithmic structure would perform using current data and variables reflective of today's population and service environment.

It is important to recognize that while algorithms improve consistency and objectivity in decision-making, they are inherently constrained by their reliance on historical data. No algorithm can fully capture individual circumstances or all contextual variables influencing outcomes. As such, algorithmic results should be viewed as informed estimates, useful for guiding decisions but not as absolute or definitive determinations.

4.4 Stakeholder Engagement

Stakeholder engagement included a broad and diverse set of participants representing the IDD HCBS community across Florida. Input was gathered from self-advocates, family members, service providers, advocacy organizations, statewide associations, and researchers. These stakeholders provided insights into the experiences of waiver participants across a variety of settings, including rural, suburban, and urban communities, in family home settings to residential treatment, and from multiple geographic regions throughout the state.

The discussions captured perspectives on service delivery, accessibility, and program effectiveness for a wide range of waiver recipients, ensuring representation of diverse needs and circumstances. By incorporating these varied viewpoints, the analysis reflects the real-world experiences of Florida's IDD HCBS population, highlighting the challenges and opportunities present across different communities and regions.

Common themes across stakeholder groups included:

- A desire for increased accuracy for service costs that adjust to rising costs of care for service providers
- Larger initial allocations that meet client needs to avoid prioritizing which essential services can be selected – the allocation of most clients is lower than their needs
- Increased offerings for a wider range of services for school-aged children
- Adjustments over time to accommodate increased costs for the aging population
- A more comprehensive understanding and efficient processing of Significant Additional Need (SAN) requests
- Increased support for families as they navigate the iBudget waiver process

Most participants believed that Florida covers a wide range of services that represent the needs of the IDD HCBS community. Self-advocates interviewed found that the process to complete the iBudget waiver has become easier to understand. Many participants shared that the provider community in Florida is a strong and committed group of organizations and individuals providing compassionate and valuable support.

However, participants also expressed the desire for an increase in the frequency of algorithm validation requirements as the needs of IDD clients evolve and the costs of services change over time. Additionally, service providers had a strong desire for more effective and supportive communication channels from APD to the providers to increase efficiency in the service coordination efforts and the SANs process.

4.5 Key Assumptions and Limitations

The following assumptions and limitations provide context for the analysis and interpretation of the findings. Together, these statements clarify the boundaries of the analysis and provide facts regarding the confidence and applicability of the conclusions.

- **Rate Integration:** The recommended algorithm does not leverage service rates in its predictor set but rather relies on historical expenditure data to infer the costs of services. As such, the model will require recalibration over time to ensure it remains in line with the service cost landscape.
- **Data Representativeness:** Historical expenditure and assessment data are assumed to capture current operational conditions with reasonable fidelity. However, shifts in service delivery models, regional pricing, and provider availability mean that past cost structures no longer fully represent the range of current outcomes. The predictive signal of the data remains consistent, but its explanatory power has narrowed.
- **Data Quality and Completeness:** Source files from iConnect and claims repositories are assumed accurate and internally consistent after standard data-quality checks. Missing or anomalous records are filtered before estimation. The remaining measurement error contributes to unexplained variance but does not systematically bias the coefficients.
- **Stability of Relationships:** The statistical form linking assessed need (via QSI and related variables) to expenditure is assumed approximately stable over short horizons. In practice, that relationship has weakened as individualized planning and provider heterogeneity introduce new, non-assessment sources of variation. The convergence of R^2 values across multiple model families indicates that this instability reflects genuine structural change rather than model misspecification.
- **Relevance of Predictors:** The selected predictors, particularly the QSI domain scores and living-setting indicators, remain conceptually relevant to support needs but explain a smaller share of total cost than in earlier calibrations. The models remain reliable in how they measure needs, but their practical impact on costs has decreased because approval decisions now take many other factors into account.
- **Independence of Observations:** Each record is treated as an independent budgeting unit. Some latent clustering by provider or region may persist, but cross-validation and random sampling minimize systematic dependency effects on parameter estimates.
- **Unobserved Confounders:** The models assume that major determinants of cost are observed within the dataset. Nonetheless, emerging administrative and environmental influences, such as provider market dynamics or regional wage differentials, introduce residual confounding beyond the reach of assessment data alone.
- **Policy and Regulatory Alignment:** All models operate within current Florida APD, Florida Agency for Health Care Administration, and Medicaid waiver rules. Estimates are valid only under the existing service definitions and allocation framework; regulatory or programmatic changes would require re-estimation.

4.6 Performance Comparison

The performance metrics presented in this report differ fundamentally from those presented in Niu and Tao, necessitating careful interpretation when comparing model performance across the two analyses. The 2015 study did not employ train-test splitting and did not report out-of-sample validation metrics. The reported R^2 value represents in-sample performance. The absence of a holdout test set means that the reported performance metrics reflect model fit rather than its predictive ability.

In contrast, the analysis in this report adopts modern machine learning practices to assess predictive performance. All models report both training metrics (in-sample and analogous to the 2015 results) and out-of-sample results. The out-of-sample, or test metrics, serve as the authoritative measure of predictive capability. As such, a direct comparison of the Niu and Tao results with the results of this report is not possible.

4.7 Recommended Interpretation Framework

Given the methodological differences, it is recommended that the following interpretative framework be used to contextualize results:

1. **Primary Benchmark:** Use Model 1 test R^2 (not the 2015 in-sample R^2) as the performance target for alternative algorithms. Model 1 represents the 2015 model formulation with contemporary feature selection and coefficients (without outlier exclusion). Model 0 (an exact re-creation of Model 5b on current data) is used as a benchmark comparison for the impact analysis to enable comparison of current state budgets to potential budgets based on the recommended model.
2. **Architectural Improvements:** Compare alternative models (2-9) to Model 1 test R^2 to assess whether different statistical approaches outperform the linear specification. Only test set comparisons are valid; training performance is uninformative for model selection.
3. **Historical Context:** Recognize that the 2015 in-sample $R^2 = 0.7998$ is not directly comparable to any metric in this report. It does not reflect true predictive capability and reflects a different population (2013-14 data vs. 2023-25 data).

4.8 Outliers

In healthcare cost prediction, apparent outliers often represent legitimate high-need individuals rather than data anomalies revealed through heavy-tail distributions,[2][3] and their exclusion risks systematically under-funding vulnerable populations. While outlier removal is common practice in predictive modelling to improve statistical fit, this practice is unfitting when predictions directly inform resource allocation decisions, as excluding high-cost cases from model training leads to biased estimates that fail to account for the full spectrum of care needs.[4] From both a statistical and ethical perspective, retaining all clients in the models

[2] Anirban Basu and Willard G. Manning. "Issues for the Next Generation of Health Care Cost Analyses". In: Medical Care 47.7 Supplement 1 (2009), S109–S114. doi: 10.1097/mlr.0b013e31819c94a1.
[3] W. G. Manning, A. Basu, and J. Mullahy. "Generalized modeling approaches to risk adjustment of skewed outcomes data". In: Journal of Health Economics 24.3 (2005), pp. 465–488.
[4] M. B. Buntin and A. M. Zaslavsky. "Too much ado about two-part models and transformation? Comparing methods of modeling Medicare expenditures". In: Journal of Health Economics 23.3 (2004), pp. 525–542.

ensures that budget algorithms remain representative of the true population heterogeneity[5] and avoid systematically disadvantaging individuals with complex support requirements.

As such, all alternative algorithmic models use 100% of the available data, including outliers.

[5] Sherri Rose. "A Machine Learning Framework for Plan Payment Risk Adjustment". In: Health Services Research 51.6 (2016), pp. 2358–2374. doi: 10.1111/1475-6773.12464.

5 Assessment Findings

The current algorithm, Model 5b, operates as a multiple linear regression model that calculates individual budget allocations based on a square-root transformation of FY 13-14 claims data. This approach incorporates 21 independent variables spanning living settings, age categories, and QSI assessment scores that evaluate behavioral, functional, and physical support needs. The analysis revealed that there is a temporal disconnect between the algorithm's FY 13-14 data foundation and current service delivery realities. It should be noted, however, that APD continues to conduct individual reviews to ensure services match individualized needs.

summarizes key performance factors used to evaluate Model 5b. These metrics provide insight into how well each model explains variation in the data, the magnitude of prediction errors, and the overall robustness of the model's output. Together, they help assess the suitability of each approach for accurately reflecting participant needs and guiding data-informed decision-making.

Table 2: Model 5b Assessment[6]

Performance Factors	Model 5b (2015 reported by Tao & Niu)	Model 0 (Model 5b Evaluated on FY 2025 Data)
R^2 [7]	0.7998 (In-sample)	0.2528 (Out-of-sample)
Root Mean Squared Error (RMSE) ($) (Square Root Scale)	30.82	92.62
Outliers (%)	9.40	0%[8]

highlights the differences in model performance over time. The initial model achieved a high level of predictive fit according to Tao and Niu (2015). However, when the model was applied to more recent data, performance decreased. These changes suggest that, although the original model may have explained a significant portion of the variation in the earlier dataset, according to Tao and Niu, its predictive accuracy is diminished when applied to the present day.

5.1 Current State Assessment Fit to Expenditure

The current Model 5b algorithm relies on FY 13-14 expenditure data, creating a temporal gap of more than 11 years from the present implementation. This temporal disconnect violates statistical assumptions and expectations. The assumption of parameter stability over this extended period is statistically untenable given documented changes in:

- Service cost inflation of approximately 30% increase over the period
- Demographic shifts in the disability population
- Evolution in service delivery models and community-based care approaches
- Changes in regulatory requirements and quality standards

[6] R^2 measures how well a model explains the variation in the data. RMSE measures the average magnitude of prediction errors. Outliers measure the proportion of data points that deviate significantly from the pattern predicted by a model.
[7] In-sample performance measures how accurately the model fits the data it was trained on, while out-of-sample performance evaluates how well the model predicts new, unseen data.
[8] Model 0 results reported with outliers retained in data set; results showed the exact same predictive performance regardless of outlier exclusion

The mathematical implication of this temporal gap can be expressed as:

Equation 1: Model 5b Temporal Gap

$$\text{Age(Data)} = 2025 - 2014 = 11 \text{ years} \gg \text{Acceptable threshold}$$

When recent expenditure patterns are compared to Model 5b predictions, the algorithm demonstrates systematic deviations that indicate deteriorating model fit over time. The original R^2 value of 0.7998 was achieved using 2013-14 data after removing 9.40% of cases as outliers. However, this performance metric does not reflect the current predictive accuracy given updated data.

This parameter drift manifests in several observable patterns:

- Systematic underestimation of costs for intensive behavioral support services
- Overestimation of residential habilitation costs in certain categories
- Failure to capture emerging service modalities that were not present in 2013-14
- Inability to reflect current workforce costs and provider rate structure

Provider rate costs increased more than ten times the average SANs allocation over five years. Similarly, the rate of provider cost increases has outpaced growth in appropriated funds, which from FY18-19 to FY22-23 increased by 35.00%.

This analysis suggests a complex operating environment that complicates the iBudget system's ability to provide efficient and effective service delivery.

6 Alternative Algorithms

Based on the findings of the current state assessment, two key areas for improvement were identified, including:

- **Statistical Factors:** The linear regression approach and the significance of some input variables could be strengthened based on recent data, which may afford expansion of independent variables.
- **Methodological Approach:** The statistical methods underlying Model 5b indicate technical competency within traditional regression frameworks; however, there is an opportunity to be more accurate using another statistical method.

Based on the findings from the current state assessment, seven alternative algorithms were evaluated for potential replacement with the current algorithm, organized into three tiers based on their mathematical composition. provides an overview of the alternative algorithms. Each was evaluated on accuracy, reliability, robustness, sensitivity to data issues, feasibility of implementation, regulatory alignment, and overall practicality of the change for APD's implementation.

Table 3: Overview of Alternative Algorithms[9]

Model Name	Model Description	Test R^2	RMSE	Mean Absolute Error
Model 1: Re-estimated Linear Regression	Maintains the exact Model 5b structure while updating and re-specifying coefficients with current, with all observations retained and no outliers removed. This represents the safest implementation path with little regulatory risk. The primary advantage is current state regulatory compliance with minimal stakeholder disruption. This model serves as the baseline of performance for models 2-9.	0.4931	$32,359.08	$21,350.20
Model 2: Generalized Linear Model with Gamma Distribution	Replaces square root transformation with a log-link function, naturally accommodating right-skewed expenditure data. This approach eliminates back-transformation bias. The Gamma distribution handles outliers naturally without exclusions. Implementation requires six to 12 months, including regulatory rule updates to specify the link function. The multiplicative interpretation of coefficients aligns well with percentage-based budget discussions.	0.4259	$34,461.43	$23,897.37
Model 3: Robust Linear Regression	Uses Huber M-Estimators to represent the optimal balance between innovation and compliance. It includes all clients through	0.4977	$32,234.42	$21,417.24

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[9] Models 7 (Quantile Regression), 8 (Bayesian Linear Regression), and 10 (Deep Learning Neural Network) were evaluated as part of the analysis. However, they did not produce single budget allocations as required in section 393.0662(1), FS, for iBudget clients and were therefore excluded from further analysis.

Model Name	Model Description	Test R^2	RMSE	Mean Absolute Error
	automatic outlier downweighing rather than exclusion. Each client receives a weight between 0 and 1, indicating data quality. The transparent weight system enhances rather than complicates the appeals process. Implementation requires six months with moderate training requirements.			
Model 4: Weighted Least Squares	Addresses heteroscedasticity through variance-based weighting. However, significant equity concerns arise as weights could create systematic bias across demographic groups. Implementation requires 12-18 months with extensive fairness testing and continuous monitoring. The approach offers superior efficiency for stable cases but may disadvantage high-need iBudget service waiver clients with variable costs.	0.5169	$31,610.80	$21,950.05
Model 5: Ridge Regression	Applies L2 regularization to handle multicollinearity among QSI variables. While offering the highest stability, the shrinkage concept proves difficult to explain to non-technical audiences. The requirement to retain all predictors aligns with current regulations, though penalty parameter justification remains challenging.	0.5202	$31,502.71	21,970.14
Model 6: Log-Normal Regression	Uses natural log transformation, which Box-Cox analysis indicates as superior to the square-root. Regulatory approval requires definitive statistical evidence of superiority over the current transformation. Retransformation bias must be carefully managed using smearing estimators or parametric corrections.	0.4598	$33,429.28	$23,181.65
Model 9: Random Forest	Averages the predictions of 150 decision trees to arrive at a final prediction. This model has the benefit of not assuming a distribution on the data, which allows it to better observe and account for interactions and nonlinearities in the data. The model is fully compliant with all salient Florida and federal regulations. It achieves the highest improvement in predictive accuracy over Model 1 (33%).	0.6575	$26,617.51	$18,709.44

7 Additional Waiver Services

Florida's iBudget program offers a broad array of HCBS waiver services designed to meet the diverse needs of participants across the state. To identify potential enhancements, the study included a review of HCBS programs in other states, focused on those with similar population sizes and those offering services mentioned in stakeholder interviews, to determine whether additional services may be appropriate to adopt in Florida. If the recommended algorithm is adopted, the actual costs of the new services, as billed by providers for client services, would be taken into account in the data when the algorithm is updated or retrained.

Currently, the HCBS program provides categorical services that help individuals live independently, improve daily functioning, and maintain health and well-being, including:

- Life Skills Development
- Supplies and Equipment
- Personal Supports
- Residential Services
- Support Coordination
- Wellness and Therapeutic Supports
- Transportation
- Dental Services

The results of the services analysis indicated that many services offered in other states are provided in some fashion in Florida. Four types of services were identified that either represent unique offerings or would enhance Florida's existing, similar services. , beginning on the next page, outlines the identified services APD may consider adding to the current iBudget waiver program in the future.

Should APD determine that the inclusion of these, or other, services is appropriate to incorporate into Florida's HCBS waiver, the following activities should be considered:

- How the service integrates into the current service array, including the category and scope of service types (such as living setting, in-home supports, etc.)
- Estimation of the potential number of iBudget clients who may utilize the services
- Identification of the actual costs of services in the Florida system of care and the corresponding potential need to request additional program funding via a Legislative Budget Request
- Addition of the new service in the Medicaid waiver, which requires federal approval
- Addition of the new service to the existing iBudget system infrastructure, including the HCBS handbook, staff, and waiver support coordinator training, and public education

In addition to these activities, the adoption of additional services would include the requirement for changes to the Florida Administrative Code, which may create administrative, financial, and legal barriers. The complex regulatory frameworks between federal and state laws may create complexities for service additions, potentially causing conflict or creating ambiguity, which would slow down the ability to implement additional services.

Table 4: Additional Service Considerations

<table>
<tr><th>Service</th><th>General Service Description</th><th>Service Gap Comparison</th><th>Relevant Florida Service Category</th><th>Potential Algorithmic Related Variables</th><th>Estimated Cost of Service Peer States</th></tr>
<tr><td>Host Home</td><td>A host home is a private residence in a residential area in which the occupant, owner, or lessee provides Community Residential Alternative (CRA) services to persons with developmental disabilities who are not related to the occupant, owner, or lessee by blood or marriage.

Georgia's service costs are provided based on a capped cost of services provided.

Texas service costs are based on the level of care requirements and are broken out into a cost per day for the level of care required in the host home.</td><td>This service (residential option) is currently not offered in Florida.</td><td>Residential Services</td><td>Living Setting: Independent Living & Supported Living</td><td>Georgia:
$155.56/day
$4,200/month
$50,402/year

Texas:
Intermittent
$72.56/day
Limited
$76.14/day
Extensive
$94.07/day
Pervasive
$119.18/day
Pervasive+
$147.84/day</td></tr>
<tr><td colspan="6">Service Effectiveness: A comparative analysis of Host Home Care vs. Traditional Care Facilities in Texas identified that Host Homes offer more personalized, family-like environments, which help to foster a deeper connection and understanding of the individuals' needs and preferences. Additionally, host homes offer a space where individuals have more emotional comfort and warmth when compared to a traditional care facility, allowing individuals to feel more "at home." Host homes also offer strong community integration, allowing individuals to experience social interaction and engagement within the community more easily than if they were in a traditional care facility.

While host homes offer many valuable opportunities for individuals with lower levels of care needs, it is not always the best option for individuals with very complex medical needs or those who require specialized medical equipment and around-the-clock clinical monitoring. Overall, host homes have shown their effectiveness for increasing the quality of life for individuals, supporting stronger community integration, and demonstrating cost-efficiency as they tend to have lower operational costs than a traditional care facility. [10]</td></tr>
</table>

[10] Jenkins, M. (2023, November 26). *Host Home Care vs. Traditional Care Facilities: A Comparative Analysis*. Above & Beyond Caring. https://abchcs.com/host-home-care-vs-traditional-care-facilities-a-comparative-analysis/

Service	General Service Description	Service Gap Comparison	Relevant Florida Service Category	Potential Algorithmic Related Variables	Estimated Cost of Service Peer States
Training and Counseling for Unpaid Caregivers	Training for unpaid caregivers is a service provided through the state to support caregivers who are typically family members and is usually provided at no cost to the family. Training for the caregivers is tailored based on the level of support the individual client needs. Illinois service costs are based on an hourly rate for the counseling provided to the unpaid caregiver. California's service cost is based on the benefits a caregiver receives by participating in the Cal Grows program.	This service is currently not offered in Florida through the iBudget program.	Personal Supports	N/A	**Illinois:** Counseling Only $33.13/hour **California:** Participant Benefit $1,088/total **Michigan:** Cost not available

Service Effectiveness: Specific studies for caregiver training and counseling in the HCBS space are limited in scope and number. However, there is evidence suggesting the importance and effectiveness of this service being provided to caregivers to improve the overall quality of life for both the client and their caregiver. Oversight and training are critical components of a successful caregiver program. California utilizes service delivery either through an Agency Model, in which contracted entities provide services, or through a Self-Directed Model. Service delivery, regardless of the model, is structured around the person-centered assessment of need based on Section 2401 of the Affordable Care Act. Each county submits a plan identifying annual goals with quality improvement and assurance oversight. According to a study by Westat for the Administration for Community Living, responses showed that mental health is correlated between caregivers and recipients; recipients with better mental health had caregivers with better mental health and fewer emotional problems. Greater care recipient satisfaction with social activities was also related to higher caregiver quality of life rating.[11] Well-designed randomized clinical trials have shown that effective caregiver interventions tend to share several characteristics, including assessments of caregiver risks and needs, tailored interventions that address multiple areas of risk or caregiver need and preferences, and active involvement of caregivers in skills training. The research also suggests the potential that some caregiver interventions reduce the resource use of care recipients by delaying nursing home placement, reducing re-hospitalizations, and shortening hospital stays.[12] Preliminary studies related to training and counseling for caregivers have shown positive results that may lead to improved mental health, increased client satisfaction, and reduced reliance on institutional settings.

[11] Avison, C., Brock, D., Campione, J., Hassell, S., Rabinovich, B., Ritter, R., Severynse, J., & Yang, D. (December 5, 2018). Outcome evaluation of the National Family Caregiver Support Program (Final Report). Westat. Administration for Community Living. https://acl.gov/sites/default/files/programs/2018-12/Caregiver_Outcome_Evaluation_Final_Report.pdf

[12] National Academies of Sciences, Engineering, and Medicine. (2016). 5 Programs and supports for family caregivers of older adults. *Families caring for an aging America* (pp. 159–200). The National Academies Press. 5 Programs and Supports for Family Caregivers of Older Adults | Families Caring for an Aging America | The National Academies Press

Service	General Service Description	Service Gap Comparison	Relevant Florida Service Category	Potential Algorithmic Related Variables	Estimated Cost of Service Peer States
Remote Support/ Monitoring	Remote Support allows an off-site direct service provider to monitor and respond to a person's health, safety, and other needs using live communication, while offering the person more independence in their home Remote Support uses two-way communication in real time, just like Skype or FaceTime, so a person can communicate with their providers when they need them. A person can choose different supports like sensors that call for help if someone has fallen or cameras that help monitor who is visiting a person's home. This service is combined with Assistive Technology.	Remote support/monitoring is a service currently supported through the iBudget. Based on the service description, it does not cover additional technologies (i.e., cameras outside the home) outside of Personal Emergency Response Systems.	Supplies and Equipment	Q23	**Ohio:** Unpaid Backup: $8.99/Hour Paid Backup: $13.99/Hour Consultation: ~$137.44 (based on outcomes) Device and Service: $75/Month (per device)
Service Effectiveness: Remote monitoring supports independence and choice by allowing people with disabilities to live more independently in their homes.[13,14] The use of these services have reported positive outcomes, including greater autonomy, ability to make decisions without in-person support, and remaining in the community longer. In Ohio specifically, the remote support services allow 24/7 monitoring which limits intrusive staff visits, supporting self-directed schedules for adults. Additionally, remote support can reduce the need for in-person staffing, which may lower per-person service costs while still maintaining oversight, although empirical cost-comparison evidence is limited.[10,15]					

[13] Friedman, C., & Rizzolo, M. C. (2013). Electronic video monitoring in Medicaid home and community-based services waivers for people with intellectual and developmental disabilities. *Journal of Policy and Practice in Intellectual Disabilities*, 10(1), 1–8. https://doi.org/10.1111/jppi.12008
[14] Tanis, E. S. (2023). Expanding the use of remote supports for people with intellectual and developmental disabilities. *Nisonger Center White Paper*. The Ohio State University. Retrieved from https://nisonger.osu.edu/wp-content/uploads/2023/03/expanding-the-use-of-remote-supports-whitepaper.pdf
[15] Clausen, M. (2023, June 27). *Remote supports for people with disabilities*. The Council on Quality and Leadership. Retrieved from https://www.c-q-l.org/resources/newsletters/remote-supports-for-people-with-disabilities/

Service	General Service Description	Service Gap Comparison	Relevant Florida Service Category	Potential Algorithmic Related Variables	Estimated Cost of Service Peer States
Peer Mentorship	Peer Mentorship is support provided by peers to promote self-advocacy and encourage community living among the disabled population. The goal of this service is to instruct and advise on issues and topics related to community living. The Peer mentor describes real-world experiences as examples and serves as a model for successful community living and problem-solving. In Colorado, a peer mentor is not someone who is a part of the same program or service location as the person receiving the service.	This service is used for training but is not currently offered to clients in Florida through the iBudget program. Peer mentorship programs are utilized through DCF. This may serve as a potential model for APD service category in the iBudget program. Peer mentorship is SAN eligible.	Life Skills Development	N/A	**Colorado:** $26.04/Hour
Service Effectiveness: Mentorship can foster a sense of community and belonging, provide support, and role-modeling to navigate challenges, such as providing mentor training, carefully matching participants, and ensuring consistent, quality relationships to achieve the best outcomes. Peer mentoring is effective for people with disabilities, enhancing social-emotional well-being by reducing isolation and stigma, while improving life skills like self-advocacy and decision-making. Peer mentorship programs are most successful when rehabilitation professionals and peer mentors collaborate to provide structured program activities and interventions that are meaningful and engaging for participants.[16] Evidence suggests that mentorship programs may be effective for helping youth with disabilities transition to post-secondary education or employment.[17] Mentoring was found to have a significant and positive impact; youth with LD/ADHD exhibited significantly more impairments in self-esteem, interpersonal relations, and depression without mentoring over the semester of an academic year.[18] Changes in self-esteem and depression were related to mentee-perceived mentorship quality and appeared to be significant regardless of gender, age, family affluence, and relationship with parents.[19] Perceived quality of the mentoring relationship, and not just the mentoring content, is important in the mentoring impact, which reinforces the need for adequate training or peers. Research in the use of peer mentoring for the disabled is limited but shows promise for youths and students with conditions such as ADHD and other mental health challenges.					

[16] Ehrlich-Jones LS, Crown DS, Tomazin SE, Wong J, Kallish N, Wafford QE, Heinemann AW. Use and benefits of peer mentoring in support of employment for persons with physical disabilities: a systematic review. Disability and Rehabilitation. 2025 Sep;47(19):4896-4903. https://pubmed.ncbi.nlm.nih.gov/40265265/

[17] Lindsay S, R Hartman L, Fellin M. A systematic review of mentorship programs to facilitate transition to post-secondary education and employment for youth and young adults with disabilities. Disability and Rehabilitation. 2016 Jul;38(14):1329-49. https://pubmed.ncbi.nlm.nih.gov/26497325/

[18] Haft SL, Chen T, Leblanc C, Tencza F, Hoeft F. Impact of mentoring on socio-emotional and mental health outcomes of youth with learning disabilities and attention-deficit hyperactivity disorder. Child Adolescent Mental Health. 2019 Nov;24(4):318-328. https://pmc.ncbi.nlm.nih.gov/articles/PMC6812582/#S21

[19] Haft SL, Chen T, Leblanc C, Tencza F, Hoeft F. Impact of mentoring on socio-emotional and mental health outcomes of youth with learning disabilities and attention-deficit hyperactivity disorder. Child Adolescent Mental Health. 2019 Nov;24(4):318-328. https://pmc.ncbi.nlm.nih.gov/articles/PMC6812582/#S21

8 Algorithm Recommendation

Model 9 utilizes Random Forest regression, an ensemble learning technique that combines predictions from 150 decision trees trained on bootstrap[20] samples of the data (a method that helps the data become amenable to random sampling methods, such as what is required for a Random Forest regression). This non-parametric approach captures complex non-linear relationships and feature interactions automatically, without requiring explicit mathematical specification, while maintaining robustness to outliers and extreme values.

Each tree is trained on a random subset of the data, and at each split, a random subset of features is considered, which reduces overfitting and improves the model's ability to generalize to new data. For regression tasks, the model's prediction is the average of all tree outputs, while for classification tasks, the majority vote across trees determines the predicted class. For this regression model, averaging of tree outputs was used.

Random Forests are widely used due to their robustness, scalability with large datasets and many features, and their ability to provide feature importance insights, highlighting which variables most strongly influence predictions. As a result, Model 9 demonstrates improved predictive accuracy over Model 1. Model 1 is the baseline as it retains the original Model 5b structure but re-estimates coefficients using current data, new predictors, and all observations without excluding outliers, to assess how the existing algorithm performs with today's population and service environment. This model can be recalibrated as desired, using sufficient statistical experience.

Model 9 delivers substantial improvements over the baseline, achieving a lower error rate (RMSE reduced by approximately 18%), higher predictive accuracy (approximately 33% improvement compared to Model 1), and demonstrating high feasibility for implementation within existing infrastructure and workflows, as seen in .

Table 5: Model 9 Comparative Performance

Performance Factors	Model 1	Model 9	Comparison
Test R^2	0.4931	0.6575	Approximately 33% improvement
RMSE ($)	32,382.10	26,617.51	Approximately 18% reduction
Outliers Removed (%)	0.00	0.00	No exclusion

The predictions generated by a Random Forest model are calculated by aggregating the outputs of all individual decision trees. For regression tasks, the predicted value for a given observation is the average of the predictions from each tree, as shown in .

[20] A bootstrap sample is a random sample drawn with replacement from the original dataset, used to estimate the variability or confidence of a statistic or model.

Equation 2: Model 9, Random Forest

$$\hat{y}_{\mathrm{RF}}(x) = \frac{1}{B}\sum_{b=1}^{B}\hat{y}_b(x)$$

Where *B* is the number of trees (150 in this implementation) and $\hat{y}_b(x)$ is the prediction from the *b*-th tree.

8.1 Key Findings

An analysis of Model 9's predictive performance reveals important patterns across different consumer characteristics and cost profiles:

- **Living Setting:** Performance varies across living settings, reflecting differences in cost structures and levels of support intensity.
- **Age Groups:** Model performance is consistent across age groups, indicating that age-related features effectively capture cost differences.
- **Cost Quartiles:** Accuracy varies by cost level, with the model performing best in the middle quartiles where the majority of observations are concentrated.

These findings highlight how Model 9 adapts to diverse client profiles while maintaining robust predictive accuracy across key dimensions.

8.2 Limitations

An algorithm is designed to generate generalized predictions based on patterns identified in historical data. While such models can provide valuable insights and improve consistency in decision-making, they cannot account for every individual circumstance or future change in context. As a result, algorithmic outputs should not be interpreted as exact or definitive; some degree of variance or error is inherent and expected in all predictive modeling.

Model 9 demonstrates several key strengths that make it a robust and reliable tool for budget prediction. Its robustness stems from the ability to naturally handle outliers without requiring their exclusion, ensuring that all clients, including high-cost or unusual cases, receive evidence-based predictions. This capability allows the model to accommodate legitimate extreme support needs, enhancing the fairness, transparency, and defensibility of budget allocations. Transparency is further supported through feature importance rankings, providing stakeholders with interpretable insights into the key drivers of predicted outcomes. Stakeholders may initially perceive the model as a "black box," though when paired with appropriate explainability tools, Model 9 meets regulatory compliance requirements of section 393.0662, FS, ensuring accountability and defensibility.

Despite these advantages, several implementation considerations should be acknowledged. Staff will need comprehensive training to understand ensemble methods (algorithmic models relying on results from an "ensemble" of other models) and the use of explainability tools. Additionally, Random Forests have a limitation in extrapolating beyond the range of training data: predictions are constrained by the minimum and maximum values observed in the training set, which may reduce accuracy for previously unseen client profiles. Additionally, the model does not directly ingest service cost data but rather infers it based on historical data. To address these concerns, the model should be regularly retrained with updated data to reflect evolving trends in service costs and ensure continued reliability.

While predictions with Random Forests are fast, the model requires greater computational resources for training and storage compared with simpler linear models. For example, training may take approximately 1.94 seconds, compared with less than one second for an ordinary least squares (OLS) model, and 150 decision trees must be stored rather than a single set of coefficients. Implementation also requires a compatible computing environment, such as Python with scikit-learn. Despite these requirements, modern computing infrastructure can easily support the model's operations.

To further enhance transparency and trust, several explainability tools should be applied:

- **SHapley Additive exPlanations (SHAP) Values:** Quantify each feature's contribution to an individual prediction, providing insight at the observation level.[21]
- **Partial Dependence Plots (PDPs):** Visualize the average effect of each feature across the dataset, highlighting general trends.
- **Individual Tree Paths:** Trace the decision path for a specific observation, offering a detailed view of the model's logic.

Implementing these tools is essential not only for regulatory compliance but also for effectively communicating results to stakeholders, mitigating the "black box" perception, and ensuring the model can be confidently applied in practice. Summarized results are included in .

Table 6: Summary Specification

Component	Specification
Algorithm	Random Forest Regression
Transformation	None
Outlier Method	None (100% inclusion)
Features	53 (Analysis-selected features minus County)[22]
Training Time	1.94 seconds
Prediction Time	< 1 ms per consumer
Memory Requirements	150 trees storage

The Scientific Report in the Appendix provides additional statistical information, especially regarding the SHAP values.

-

[21] SHAP values provide mathematically rigorous feature attribution, transforming Model 9's ensemble predictions into transparent, dollar-scale explanations as required by F.S. 393.0662. SHAP values provide a mathematically consistent framework that decomposes each prediction into additive feature contributions. This allows directional interpretation (positive or negative impact), person-specific explanations, and explicit accounting for feature interactions, producing results that are more transparent and policy relevant for the iBudget analytical framework.

[22] County indicator was found to degrade out-of-sample performance due to the non-parametric nature of a Random Forest

9 Impact Analysis

The impact analysis describes potential effects of the recommended algorithm, Model 9 Random Forest, on the iBudget system, including its funding at the individual level, the statewide iBudget System budget, policy and procedure impacts, and other implementation considerations.

For model comparison purposes, the currently used Model 5b's performance when predicting on 2025 data is referred to as Model 0 in this impact analysis.

9.1 Supplemental Funding Needs

The current actual cost for the iBudget system is $1,680,682,854, which is the sum of services provided in FY 24-25 according to the APD database. The estimated supplemental funding needs are compared to the current cost and defined as follows:

- **Total Actual Cost:** The sum of all observed expenditures in the historical dataset for the base year. This represents APD's actual fiscal outlay for waiver services and serves as the empirical baseline ($1,680,682,854).
- **Total Predicted Cost:** The sum of the model's estimated allocations for each individual, based solely on assessed need and model parameters. This reflects the theoretical distribution of funds if the predictive algorithm were implemented without any legal or policy constraints.
- **Total Maximum Cost:** This measure enforces statutory protections against reductions in individual allocations by setting each person's projected cost to the greater of the actual and predicted values. The Total Maximum Cost, therefore, guarantees that no participant receives less than their current level of support, ensuring compliance with regulatory and policy requirements.

Table 7: Projected Changes to Total iBudget System Funding, presents a comprehensive comparison of all models relative to actual costs. This comparison reveals each model's predictive accuracy and its implications for budget allocation. Based on the predicted maximum cost, Model 9 would require an additional $266,943,053 (15.9% increase) compared to the actual current costs.

Table 7: Projected Changes to Total iBudget System Funding

Model	Predicted Cost	Percent Difference from Actual Cost	Predicted Maximum Cost	Percent Difference from Actual Cost
Model 0 (Model 5b evaluated on 2025 data)	$1,375,473,878	-18.2%	$2,051,817,703	22.1%
Model 9	$1,579,418,490	-6.0%	$1,947,625,907	15.9%

Model 9, Random Forest, produces individual budget amounts that are more reflective of the current needs of clients, which results in budgets that are different from current allocations, either an increase or a decrease in their original allocation. These changes were analyzed and are presented by the number of waiver enrollees whose budgets are estimated to increase or decrease, categorized by:

- Current total individual budget amount
- Age range
- Living setting

Tables 8, 9, and 10 quantify the expected changes in individual budget allocations across different enrollee demographics from the current state algorithm, Model 0, to the recommended state, Model 9 – Random Forest.

Table 8: Estimated Individual Budget Changes

	Enrollees Whose Budgets are Estimated to Increase or Decrease	
Type of Change	**Number**	**Percent**
Decrease*	14,016	~39.5%
Increase	21,106	~59.5%
No Change	322	~0.9%

* When Model 9 estimates a lower budget for a client, their actual allocation will remain unchanged and not be reduced. Individual budgets will not be reduced as the services funded have already been approved based on medical necessity.

Table 9: Estimated Individual Budget Change by Age Category

		Model 0 (Current State)	Model 9 (Random Forest Recommendation)		
Age Groups	**Population Size**	**Average Allocation**	**Average Allocation**	**Allocation Change**	**Percent Change**
3-20	3,119	$23,003	$23,499	+$496	+2.2%
21-30	9,360	$36,748	$44,680	+$7,932	+21.6%
31 and Over	22,965	$41,793	$47,373	+$5,580	+13.4%

Table 10: Estimated Individual Budget Changes by Living Setting

		Model 0 (Current State)	Model 9 (Random Forest Recommendation)		
Living Setting	**Population Size**	**Average Allocation**	**Average Allocation**	**Allocation Change**	**Percent Change**
Family Home	19,848	$23,547	$22,527	-$1,020	-4.3%
Independent/ Supported Living	4,546	$40,756	$46,176	+$5,420	+13.3%
Residential Habilitation 1	9,297	$54,674	$85,639	+$30,964	+56.6%
Residential Habilitation 2	170	$69,313	$72,047	+$2,734	+3.9%
Residential Habilitation 3*	1,240	$120,071	$74,986	-$45,085	-37.5%
Residential Habilitation 4*	343	$157,016	$61,118	-$95,898	-61.1%

*The prediction of these service levels is not as well accommodated by Model 9 as the other service levels. These service levels may require clients to submit SAN requests.

9.2 Technical Implementation Cost

The estimates of total technical costs for Model 9 are displayed in Breakdown. The estimated costs serve as a general framework informed by the practical implementation of comparable systems. These estimates do not include consideration of APD staffing needs ,or any external vendor support.

Table 11: Model 9 Estimated Cost Breakdown for Implementation[23]

	Unit Cost	Hours	Total Cost
Development Cost	$250	340	$85,000.00
Implementation Cost	$250	380	$95,000.00
Training Costs	$250	260	$65,000.00
Annual Operational Costs	$250	340	$85,000.00
***Three-Year Cost of Ownership**	**$250**	**1,320**	**$500,000.00**

*This includes the annual operating cost three times.

The estimated preliminary costs associated with the development phase encompass traditional software development activities, including project management, programming, and business analysis. These efforts are directed toward designing, building, and configuring the system in alignment with functional and technical requirements.

The code is provided in the scientific report. Therefore, the estimated preliminary implementation costs include activities related to system testing, deployment, and initial configuration. This category also covers software licensing or procurement expenses, as well as the labor hours required to establish and operationalize the system.

Internal training will need to be provided to technical users to support successful implementation; however, external or end-user training is not included within this cost. Rulemaking, stakeholder communication, and stakeholder training are also not included in the technical implementation cost estimate.

Following deployment, continuous system monitoring and refinement will be required to ensure optimal performance and to address any issues that may arise during operation.

9.3 Regulations

Model 9 is regulatorily sound, as it aligns with the requirements outlined in section 393.0662, FS, and would incorporate explainability tools, such as SHAP values, partial dependence plots, and individual tree paths, to ensure transparency, accountability, and defensibility, as illustrated in Figure 4: Regulatory Compliance.

[23] Technical implementation costs are detailed in the Scientific Report in Appendix Section 11.1 Scientific Report, in section 11.1.

Figure 4: Regulatory Compliance

Requirement	Status	Implementation
Individual explanations	✅	SHAP values
Feature documentation	✅	Importance rankings
Reproducibility	✅	Random seed control
Audit trail	✅	Tree decision paths
Appeal process	✅	Prediction intervals

It also meets the current requirements in 65G-4.0214, FAC, to be interpretable through feature importance, though this section of code would need to be updated to reflect the new algorithm methodology, including procedures and requirements for recalibration of the algorithmic model. The framework of Model 9, Random Forest, would support adjustments to the algorithm itself as policies change. Specifically, its non-parametric nature allows it to adapt to policy changes without model restructuring:

- If a new support type is introduced, simply add it as a feature
- If QSI scoring changes, the model automatically adjusts to new patterns
- No need to hypothesize and test specific interaction terms

9.4 Technical Deployment Strategy

It is recommended that APD implement Model 9 in a phased approach to ensure a smooth transition from the current state of operations. This phased implementation would include the approach of parallel operation as described below.

- Infrastructure Setup (~1 month): Python environment and model hosting
- Pilot Testing (~2 months): 5,000 consumer subset validation
- Parallel Run (~6 months): Side-by-side with Model 5b
- Training Program (~3 weeks): Staff education on ensemble methods
- Phase Rollout (~2 months): Regional deployment with monitoring
- Full Implementation (~1 month): Statewide deployment

Note: This timeline does not consider project planning or management time required by the current iConnect CDMS vendor, WellSky.

This deployment strategy serves as a general framework informed by the practical implementation of comparable systems. Prior to launching the algorithm, a comprehensive readiness assessment should be conducted to evaluate any changes in data, policy, system architecture, or population characteristics that could influence implementation outcomes. This review will ensure that all contextual factors are accounted for, mitigating risks and supporting a smooth, evidence-based transition to the new model.

10 Conclusion

A comprehensive analysis was conducted to evaluate the current algorithm and identify potential alternative approaches. This work incorporated multiple sources of information, including historical data and stakeholder input, resulting in a recommendation that is expected to better meet the needs of the population across diverse geographic and demographic groups. By grounding the recommendation in real-world experiences and prioritizing the perspectives of participants, the approach reinforces a people-centered framework that aims to ensure fairness and meaningful support for all individuals. The recommended model, Model 9 Random Forest, is grounded in modern data science, can be easily updated based on policy or population changes, is explainable and interpretable, and includes the use of all data points (no data exclusion).

To ensure continued accuracy and fairness, it is recommended that the algorithm undergo pilot testing before full implementation and recalibration whenever material changes occur. Specifically, recalibration should be conducted if there are significant shifts in cost structures, service utilization patterns, or population characteristics, such as when the population served changes by more than five percent. This approach promotes ongoing alignment between the model's predictions and real-world conditions, helping to maintain the integrity and equity of individualized budget allocations over time.

While this recommendation represents a significant step forward, the SANs process will continue to play a critical role in capturing individual circumstances and ensuring equitable service allocation. Because no predictive model can perfectly account for every individual's needs, the SANs process remains essential to address situations where the model may not fully capture a participant's unique circumstances.

It is also recognized that ongoing evaluation may be needed, including potential reassessment of the individual assessment tool, such as the QSI, other internal or external measures, or alternative validated tools originally developed to assess the support needs of individuals. As IDD classifications and service delivery practices evolve, it may be appropriate to consider enhancements to the variables included in the algorithm to ensure it continues to reflect the full range and diversity of participant needs, supporting informed, equitable, and data-driven decision-making.

11 Appendix

11.1 Scientific Report

The document embedded below is the full scientific report of the iBudget Algorithm Study, containing all statistical analyses and coding details.

Final Scientific Reort
11.7.2025.pdf

11.2 Current State Assessment

The current state assessment provides an evaluation of the current algorithm, Model 5b, and the fit of recent expenditures.

10.23.2025_APD
iBudget Algorithm Stu

11.3 Alternative Algorithms

The alternative algorithms report presents seven algorithmic model options for consideration of use.

10.24.2025 APD
iBudget Project_D3 Alt

11.4 Recommended Algorithm and Impact Analysis

This document details the recommended algorithm for APD's implementation and provides an analysis of its potential impacts to the iBudget system.

10.28.25_APD_iBud
get Algorithm Study

ISF Solving the future

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agency for persons with disabilities
State of Florida

Assessment of Current Algorithm

Florida Agency for Persons with Disabilities

2025 iBudget Algorithm Study

October 23, 2025

Deliverable 2 – Assessment of Current Algorithm

Table of Contents

Table of Figures

Table of Tables

Revision History

Version	Date	Author	Notes
V1	09/23/2025	ISF	D2 for APD Review
V2	09/29/2025	ISF	D2 for APD Acceptance
V3	10/23/2025	ISF	D3 Assessment Updates

Acronyms

Acronym	Definition
AHCA	Florida Agency for Health Care Administration
AI	Artificial Intelligence
AIM	Allocation Implementation Meeting
APD	Agency for Persons with Disabilities
BSum	Behavioral Status Sum
CMS	Centers for Medicare & Medicaid Services
D	Deliverable
DED	Deliverable Expectation Document
FAC	Florida Administrative Code
FHFSum	Family Home by Functional Status
FS	Florida Statutes
FY	Fiscal Year
GAA	General Appropriations Act
HB	House Bill
HCBS	Home and Community Based Services

Acronym	Definition
ILSL	Independent Living & Supported Living
QSI	Questionnaire for Situational Information
RH1	Residential Habilitation Standard
RH2	Residential Habilitation Behavior Focus
RH3	Residential Habilitation Intensive Behaviors
RH4	Residential Habilitation Special Medical
SAN	Significant Additional Needs
SBC	Schwarz Bayesian Criterion
SE	Standard Error
SLBSum	ILSL by Behavioral Status
SLESum	ILSL by Functional Status

1 Executive Summary

The Home and Community-Based Services (HCBS) iBudget system is part of Florida's Medicaid waiver system, which provides individuals with developmental disabilities the opportunity to receive care and support in their homes and communities. The iBudget uses an algorithm based on age, living setting, and information from the Questionnaire for Situational Information (QSI), along with a supplemental assessment as needed, to allocate individualized budgets that reflect each person's unique needs. The Agency for Persons with Disabilities (APD) administers the iBudget, currently serving more than 36,000 people, with more than 20,000 in pre-enrollment categories.

ISF was engaged to conduct a comprehensive analysis of the statistical and mathematical foundations of Model 5b, the algorithm currently used by APD to determine individual iBudgets, which was implemented in 2015. The current algorithm operates as a multiple linear regression model that calculates individual budget allocations based on a square-root transformation of fiscal year (FY) 13-14 claims data. This approach incorporates 22 independent variables spanning living settings, age categories, and QSI assessment scores that evaluate behavioral, functional, and physical support needs.

> The iBudget algorithm serves thousands effectively, though advances in methods and tools may present opportunities for improvement.

Based on ISF's assessment, the algorithm functions as intended within the current federal and state regulatory frameworks. The algorithm provides a legally defensible allocation method that is both interpretable and auditable. According to Nui and Tao, the creators of the original 2015 Model 5b, the algorithm's R^2 value of approximately 0.80 means the model explains about 80% of the variance in the square-root transformed expenditures. However, today the R^2 has decreased due to a lack of updates over the last decade.

Furthermore, the current methodology for outlier removal leverages standardized residual analysis for outlier detection. This approach assumes homoscedastic errors, does not distinguish between legitimate high-needs cases and data errors, and creates systematic exclusion of complex support scenarios. Due to advances in statistical methods and tools over the last decade, there may be an opportunity to improve predictions for high expenditure clients and reduce systematic bias patterns that underestimate residential habilitation categories and overestimate independent living and supported living settings, which is also a requirement of the 2025 House Bill 1103.

Finally, the current algorithm, based on expenditure data from FY 2013–14, leaves a gap of more than 11 years from present-day implementation. This timeframe may undermine statistical assumptions and expectations. In addition, the system has struggled to keep pace with service demand, as evidenced by recurring deficits and increased appropriations.

Building on current findings, ISF will continue analyzing the data to determine whether a more effective algorithm can be developed. The goal is to identify an approach that is people-centered, feasible to implement, and is still fully aligned with both state and federal regulations. The ongoing study will ensure that any proposed enhancements not only improve accuracy and fairness in budget allocation but also remain compliant, practical, and responsive to the needs of individuals served.

2 Background

The mission of APD is to support individuals with disabilities and their families in living, learning, and working within their communities by creating multiple pathways to possibilities.[1] APD serves individuals with disabilities, as defined in section 393.063(11), Florida Statutes (FS), through identifying service needs, connecting them with appropriate social, medical, behavioral, residential, and therapeutic supports, and funding the required level of services through applicable programs.

The United States Centers for Medicare & Medicaid Services' (CMS) HCBS Medicaid waiver allows the federal government to waive rules that typically apply to Medicaid programs. The use of the HCBS waiver provides states with the opportunity to achieve specific goals and offers services that would not typically be covered by Medicaid.[2] The Florida Agency for Health Care Administration (AHCA), the state's primary Medicaid administering agency, partners with APD to provide the HCBS waiver program to APD's service population.

The HCBS Medicaid waiver is administered by APD through the iBudget system, enabling APD clients to receive medically necessary support and services that facilitate living in the community. The iBudget system offers a variety of social, medical, behavioral, therapeutic, and residential services to individuals with developmental disabilities. As of 2025, there are more than 36,000 individuals enrolled in the program, with a pre-enrollment list of more than 20,000 people. Each client's iBudget amount is calculated using the allocation algorithm in Rule 65G-4.0214, Florida Administrative Code (FAC), based on age, living setting, and QSI factors,[3] plus any significant additional needs (SAN) identified in individual reviews.

During the 2025 legislative session, the Florida Legislature passed House Bill (HB) 1103, which was subsequently signed into law on June 9, 2025. This legislation requires APD to contract for a study to review, evaluate, and identify recommendations regarding the algorithm required under section 393.0662, FS, the iBudget implementing statute.

In response to HB 1103, APD engaged ISF to conduct the iBudget Algorithm Study. The study involves activities to support the development of recommendations to ensure the up-to-date and accurate allocation of resources to Florida's most vulnerable citizens, aligning with both statutory requirements and principles of person-centered care. These activities include:

- Assessment of the current algorithm, including expenditure data (Deliverable (D) 2)
- Identification of potential alternative algorithms (D3)
- Recommendation of one algorithm for APD's implementation (D4)
- Production of the iBudget Algorithm Study report as required in HB 1103 (D5 and D6)

This document, D2, provides ISF's assessment of the performance of the current algorithm used by APD, including the fit of recent expenditure data to the current algorithm based on available data.

[1] Agency for Persons with Disabilities, State of Florida. (2025, August). APD – Agency for Persons with Disabilities. Retrieved September 12, 2025, from https://apd.myflorida.com/index.htm
[2] Centers for Medicare & Medicaid Services. (n.d.). Home & Community-Based Services 1915(c). Medicaid. U.S. Department of Health and Human Services. Retrieved September 12, 2025, from https://www.medicaid.gov/medicaid/home-community-based-services/home-community-based-services-authorities/home-community-based-services-1915c
[3] Agency for Persons with Disabilities. (2015, May 21). Florida questionnaire situational information (version 4.0).

3 Assessment Approach

The strategic approach ISF used to analyze the current algorithm, and then subsequently develop D2, is illustrated in Figure 1: Assessment Approach. Each component of the approach is detailed below.

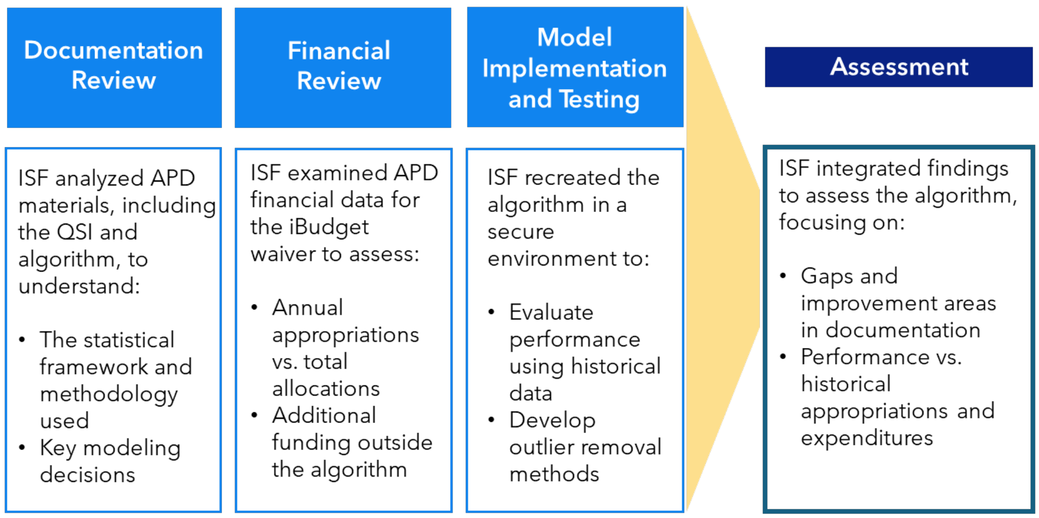

Figure 1: Assessment Approach

To support the understanding of the information and analysis in this assessment, Appendix sections 6.1 and 6.2 provide the definitions of key terms and the basics of algorithms, respectively.

3.1 Documentation and Algorithm Review

ISF conducted a comprehensive review of publicly available materials, along with all documentation provided by APD concerning the existing algorithm, its development history, financial information, and the creation and audit of the QSI instrument. A cleansed dataset was not ready during the time of the initial analysis. However, ISF will continue to refine and validate the data, incorporating updates as they become available.

Following this review, the ISF team performed an in-depth analysis of the statistical and mathematical foundations of Model 5b, the current algorithm used by APD. This analysis included the following activities:

- Evaluation of the algorithm's mathematical structure against established best practices in modern data science
- Identification of key statistical assumptions, such as data distribution, error terms, variance, documenting the defined independent and dependent variables, transformation techniques, and model selection strategies
- Identification of potential opportunities for improvement, including opportunities to leverage new technologies and state-of-the-art data analysis techniques

- Examination of the methodology used to establish the statistical framework, including an assessment of the rationale behind the inclusion and exclusion of independent variables, the algorithm's approach to outlier management, and the overarching strategy adopted by APD

3.2 Model Implementation and Testing

> The Python implementation replicates Model 5b's coefficient structure, successfully mimicking and preserving the original methodology.

Following the initial analysis of the algorithm, the ISF team applied Model 5b in a secure environment to enable algorithm validation. The Python implementation, which mimics the application of the algorithm, as currently used by APD, reproduces the exact coefficient structure of Model 5b, ensuring mathematical fidelity to the original methodology. All regression coefficients, interaction terms, and transformation procedures match the specifications of the algorithm, enabling direct comparison with the original statistical analysis.

The Python implementation was tested with mock data in JavaScript Object Notation format and returned predicted allocation amounts based on the algorithm's logic. To ensure the integrity and reliability of the implementation, ISF generated mock client-level data aligned with Model 5b's structure. The mock data maintains realistic relationships between variables, ensuring that sum scores align with individual question responses and that support needs correspond appropriately to living settings. The dataset also incorporates edge cases and boundary conditions to test algorithm robustness, including individuals with minimal support needs, maximum scoring scenarios, and atypical combinations that may occur in real-world assessments. This mock data was processed through the model to confirm the accuracy of the implementation.

Upon successful validation of how the algorithm runs with mock data, ISF then tested the model using real historical data provided by APD, including actual allocations made through the iBudget system. Once data is cleansed and validated, it will then be fed into the model, and the resulting predictions will be compared against actual allocations. This comparison will enable the calculation of error rates and the assessment of the model's average accuracy and reliability, following best practices in statistical model evaluation. As a part of the testing process, the ISF team will test the algorithm on areas beyond performance, including sensitivity to coefficient changes, tolerance to changes in policy, and differences across distinct population subgroups.

3.3 Financial Review Approach

ISF conducted a detailed analysis of historical financial data provided by APD, along with publicly available APD financial data. This analysis encompassed a review of annual financial metrics such as total appropriations, expenditures, surpluses or deficits, and the number of clients served. The specific data that informed this analysis were obtained from APD's HCBS Waiver Monthly Surplus-Deficit Report for Waiver Program Expenditures for FY18-19 to FY22-23.

An analysis was conducted to align all financial data, listed below, to Florida's fiscal year to be comparable with other budget and program documentation:

- General Appropriations Act (GAA) data is as of June 30 (end of Florida's fiscal year) for each year assessed
- In years where supplemental funding was appropriated, the "Total Adjusted GAA" amount reflects the supplemental, back-of-the-bill appropriations

Expenditure data is projected (as of June 30) through September 30 of each year to align with the Surplus-Deficit Report timeline and account for the carry forward of funds to resolve prior fiscal year billing/payments in the fiscal year the services likely occurred The results of the document and algorithm review, model implementation and testing, and financial review were then synthesized to develop the assessment documented in Section 4.

4 Current State Assessment

It is important to note that, as a fully cleansed dataset was not available at the time of initial analysis, this current state assessment is based on the information currently available. ISF will continue to refine and validate the data, incorporating updates into the assessment as available. By the time of the October 15 draft report submission, the data standardization is expected to be resolved, allowing the draft report to reflect fully accurate and validated information.

The current algorithm, Model 5b, operates as a multiple linear regression model that calculates individual budget allocations based on a square-root transformation of FY13-14 claims data. This approach incorporates 22 independent variables spanning living settings, age categories, and QSI assessment scores that evaluate behavioral, functional, and physical support needs. The assessment of the current algorithm required examination across five critical dimensions, each explored in this section:

- Section 4.1: Understanding of the current regulatory environment
- Section 4.2: Identification and refinement of variables
- Section 4.3: Outlier management methods
- Section 4.4: Fit of recent expenditure data
- Section 4.5: Evaluation of accuracy and reliability

Each dimension revealed both achievements and limitations that impact the algorithm's ability to exclusively serve today's iBudget population outside of the SAN process. The algorithm's role extends beyond mere budget calculations as it fundamentally shapes how resources are distributed, what services individuals can access, and how person-centered planning principles are implemented in practice.[4] Based on ISF's assessment of the current Model 5b, as tested, the algorithm is functioning as intended, serving a vast population within the current federal and state regulatory frameworks for iBudget clients. The allocation amounts generated by the algorithm, combined with the SAN process as appropriate, support the needs of thousands of Floridians to receive the care they need to live as independently as possible.

Even as the Model 5b algorithm may serve the needs of current iBudget system enrollees, the current state assessment identified opportunities for updates and improvements to the algorithm, including:

- Significant strides in technology and data science, including advances in data analytics techniques and data processing software to support effective analyses
- Updated legislative direction via HB 1103 that guides APD's priorities in evaluating the current algorithm and potential changes
- Advanced, current mathematical techniques that increase accuracy and reliability

[4] Person-centered planning emphasizes the individual's preferences, needs, and goals, ensuring that services and supports are tailored to the person rather than the system. [Person-Centered Service Planning in HCBS: Requirements and Best Practices]

4.1 Regulatory Environment

The current Model 5b multiple linear regression model, using the QSI and supplemented by the SAN assessment, provides an allocation methodology that is legally defensible at both the federal and state levels because it is interpretable and auditable, while remaining accountable to individuals' needs.

The current algorithm is designed to comply with both federal and state regulatory requirements. At the federal level, adherence safeguards Florida's HCBS waiver authority and secures critical Medicaid matching funds. At the state level, compliance ensures that the algorithm aligns with Florida law and policy, while equitably distributing resources to clients with developmental disabilities. This dual framework makes the iBudget system legally sustainable while upholding the rights and protections of the individuals it serves. Figure 2: Regulatory Environment provides an overview of the regulatory environment of the iBudget system.

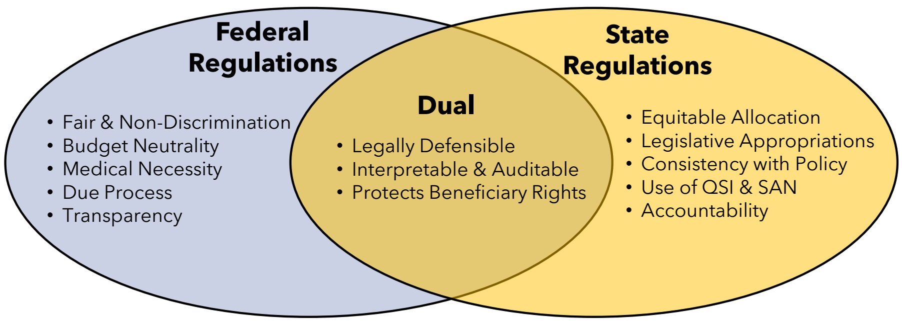

Figure 2: Regulatory Environment

The iBudget system has faced multiple legal challenges from stakeholders who questioned the fairness and validity of its methodology. However, Florida successfully defended the lawsuits because the algorithm was designed and implemented in compliance with both federal Medicaid requirements and state statutory mandates. Courts recognized that adherence to the requirements provided the necessary legal foundation for the system and ensured that the iBudget's algorithmic methodology meets the standards of fairness, transparency, and accountability.[5]

At the federal level, CMS requires that allocations be fair, non-discriminatory, and sufficient to cover medically necessary services under the HCBS waiver. Moreover, CMS requires that funding is transparent, explainable, and legally accountable.[6] The system must also demonstrate budget neutrality,[7] ensuring that total expenditures do not exceed federal limits, and guarantee due process protections for participants who wish to appeal their allocations.

[5] Office of Program Policy Analysis and Government Accountability. (2014, March). iBudget implementation continues as the Agency for Persons with Disabilities responds to legal challenges (Report No. 14-09). Tallahassee, FL: OPPAGA.

[6] McDermott Will & Emery. (2024, February 20). CMS releases guidance on coverage criteria, utilization management and use of AI. Retrieved September 19, 2025, from https://www.mwe.com/insights/cms-releases-guidance-on-coverage-criteria-utilization-management-and-use-of-ai/

[7] §1915(c)(2)(D) of the SSA requirement: Retrieved September 26, 2025, from https://www.ssa.gov/OP_Home/ssact/title19/1915.htm; https://www.medicaid.gov/medicaid/home-community-based-services/downloads/hcbs-1e-cost-neutrality.pdf

The algorithm must also comply with section 393.0662, FS, at the state level. These requirements direct APD to implement an algorithm that is reliable and valid and aligns with annual legislative appropriations while accounting for variation in individual needs.[8]

The current algorithm meets the legal requirements, and therefore any replacement must meet and exceed its performance while providing single-point budget allocations that can withstand appeals processes. Any alternatives must balance between statistical sophistication, implementation complexity, and regulatory compliance.

4.2 Variable Evaluation

Transformation bias may result in underestimating the needs of high-needs individuals while overestimating the needs of low-needs individuals, potentially affecting resource allocation and planning.

As part of the current state assessment, ISF identified and refined the dependent and independent variables used in Model 5b. The dependent variable in Model 5b is the square-root transformed FY13-14 expenditure, where Y_i represents individual expenditures, as displayed in Figure 3: Algorithm Dependent Variable.

$$\sqrt{Y_i} = \beta_0 + \sum_{j=1}^{5} \beta_j^{Live} \cdot Live_{ij} + \sum_{k=1}^{2} \beta_k^{Age} \cdot Age_{ik} + \sum_{l} \beta_l^{QSI} \cdot QSI_{il} + \varepsilon_i$$

Figure 3: Algorithm Dependent Variable

The square-root transformation of the dependent variable addresses the skewness of that data but creates systematic bias through a theorem in mathematics called Jensen's inequality. The theorem states that, as the square root function being used is concave, the results of the algorithm (the squared output dependent variable) will under- or overestimate outcomes. This imprecision becomes larger the more atypical a case is, meaning that very low-need clients may get overestimated budgets, while very high-need clients may be underestimated. This transformation bias can lead to consistent underestimation for high-needs individuals and overestimation for low-needs cases.

The independent variables are identified in Table 1: Model 5b Independent Variables. Key elements of the variables include:

- β_i (Coefficient): The fixed number that tells the algorithm how much weight or importance to give to the independent variable i. The larger the number, the higher the weight.
- SE (Standard Error): A measurement of relative precision, where the lower the SE value, the higher the precision and vice versa.

[8] Florida Legislature. (2025). Florida Statutes, section 393.0662: Individual budgets for delivery of home and community-based services; iBudget system established. Retrieved September 19, 2025, from https://www.leg.state.fl.us/Statutes/index.cfm?App_mode=Display_Statute&Search_String=&URL=0300-0399%2F0393%2FSections%2F0393.0662.html

Table 1: Model 5b Independent Variables

Variable Category	Variable	Coefficients and Precision Estimate
Living Setting	Family Home (FH)	Reference category with coefficient = 0
	Independent Living & Supported Living (ILSL)	β = 35.8220 (SE = 0.91949)
	Residential Habilitation Standard (RH1)	β = 90.6294 (SE = 0.94365)
	Residential Habilitation Behavior Focus (RH2)	β = 131.7576 (SE = 1.28906)
	Residential Habilitation Intensive Behavior (RH3)	β = 209.4558 (SE = 1.93208)
	Residential Habilitation Special Medical (RH4)	β = 267.0995 (SE = 2.71191)
Age Categories	Under 21	Reference category with coefficient = 0
	Age 21-30	β = 47.8473 (SE = 0.79766)
	Age 31+	β = 48.9634 (SE = 0.76383)
Behavioral/Functional Sum Scores and Interactions	Behavioral Status Sum (BSum)	β = 0.4954 (SE = 0.06304)
	Family Home by Functional Status (FHFSum)	β = 0.6349 (SE = 0.04891)
	ILSL by Functional Status (SLFSum)	β = 2.0529 (SE = 0.07452)
	ILSL by Behavioral Status (SLBSum)	β = 1.4501 (SE = 0.10411)
Individual QSI Questions	QSI Questions: 16, 18, 20, 21, 23, 28, 33, 34, 36, 43	Coefficients ranging from 1.2233 to 6.3555

Following the identification and refinement of the dependent and independent variables, the evaluation revealed the following:

- Some variables relevant to the algorithm's calculations demonstrated non-significance, meaning that some inputs may not provide as much meaning in the calculation of the allocation amounts as expected.
- Initial models of the data showed negative coefficients, indicating allocations may be over or under actual needs. Negative coefficients mean that as the predictor variable increases, the predicted budget allocation decreases. For variables measuring disability severity or support needs, this does not make logical sense - people with greater needs should receive more funding, not less.
- There is an opportunity to enhance the person-centered focus with additional variable incorporation.

4.3 Data Outliers

Model 5b achieves its reported performance through outlier removal. Figure 4: Accuracy Before and After Outlier Removal displays the accuracy of the algorithm before and after data outliers are removed.

$$\begin{aligned} n_{outliers} &= 2,410 \text{ (9.40\% of sample)} \\ n_{total} &= 25,615 \text{ (after outlier removal)} \\ R^2_{full} &= 0.7549 \ll R^2_{reduced} = 0.7998 \end{aligned}$$

Figure 4: Accuracy Before and After Outlier Removal

Note that R-squared, also known as the coefficient of determination, is used in statistics to measure how well a model explains the data. The closer the R-squared value is to 1, the more accurately the model explains the data. Figure 4 shows that the removal of outliers increased Model 5b's accuracy.

ISF's methodology for the identification of outliers was based on the current methodology for outlier removal, which leverages standardized residual analysis for outlier detection. This approach works as follows:

1. Apply the model to the entire dataset, including outlier cases
2. Calculate residuals, the difference between the predicted budget and the actual budget, for each datapoint
3. Datapoints with extraordinarily large residuals (Z-score greater than or equal to 3 or -3) are identified as outliers

This approach:

- Assumes homoscedastic errors—that error (in this case, the residuals) will always be roughly the same size, an assumption that does not hold in disability expenditure data
- Fails to distinguish between legitimate high-needs cases and data errors
- Creates systematic exclusion of complex support scenarios

As part of the development of Model 5b, alternative outlier detection strategies were investigated, including Model 5c, which is identical to Model 5b, except with fewer outliers removed (4.96% of cases removed instead of 9.40%). This reduction in outlier removal resulted in worse model performance and higher standard error. This represents a trade-off between statistical performance and inclusivity, which highlights fundamental tensions in the algorithmic approach. The requirement for aggressive outlier removal suggests:

- The potential presence of unmodeled, nonlinear relationships within the data
- The dataset is highly variable and includes many complex cases, which linear models often struggle to accommodate

4.4 Assessment of Expenditure Data

The current Model 5b algorithm relies on FY13-14 expenditure data, creating a temporal gap of more than 11 years from the present implementation. This temporal disconnect violates statistical assumptions and expectations. The assumption of parameter stability over this extended period is statistically untenable given documented changes in:

- Service cost inflation of approximately 30% increase over the period
- Demographic shifts in the disability population
- Evolution in service delivery models and community-based care approaches
- Changes in regulatory requirements and quality standards

The mathematical implication of this temporal gap can be expressed as:

$$\text{Age(Data)} = 2025 - 2014 = 11 \text{ years} \gg \text{Acceptable threshold}$$

When recent expenditure patterns are compared to Model 5b predictions, the algorithm demonstrates systematic deviations that indicate deteriorating model fit over time. The original R-squared value of 0.7998 was achieved using 2013-14 data after removing 9.40% of cases as outliers. However, this performance metric does not reflect the current predictive accuracy given.

$$\hat{\beta}_{2025} \neq \hat{\beta}_{2013-14}$$

This parameter drift manifests in several observable patterns:

- Systematic underestimation of costs for intensive behavioral support services
- Overestimation of residential habilitation costs in certain categories
- Failure to capture emerging service modalities not present in 2013-14
- Inability to reflect current workforce costs and provider rate structures

Furthermore, five years of recent iBudget expenditure data were reviewed to evaluate spending patterns, trends, and program outcomes, providing insight into how well the algorithm performs. The goal is to identify whether program outcomes, including budget surpluses/deficits, enrollment rates, and pre-enrollment persistence, reflect algorithmic performance or external factors.

Table 2: FY18-19 to FY22-23 iBudget Program Expenditure Metrics provides an overview of key metrics from FY18-19 to FY22-23 that drive the analysis.

Table 2: FY18-19 to FY22-23 iBudget Program Expenditure Metrics

Fiscal Year	2018-19	2019-20	2020-21	2021-22	2022-23
Total Adjusted GAA $	$442,273,857	$475,418,634	$413,776,465	$466,217,928	$632,546,817
Total Expenditures $	$481,548,988	$468,217,957	$407,407,027	$441,435,582	$585,200,658
Surplus / Deficit $ (GAA)	($39,275,131)	$7,200,677	$6,369,438	$24,782,346	$47,346,159
Clients Served #	34,732	35,073	34,864	35,207	35,565
Pre-enrollment Count #	21,631	22,848	22,744	22,578	*See Note*
SANs Allocation $	$100,443,502	$90,419,045	$66,350,513	$77,938,740	$120,206,955
SANs Clients #	6,638	5,952	3,661	3,838	5,230
Total Expenditures (State/Federal)	$1,235,570,305	$1,312,262,992	$1,269,729,605	$1,275,743,991	$1,669,556,706

Note: No pre-enrollment data was provided in the FY22-23 reports.

Total adjusted GAA reflects state expenditures per fiscal year, while "Total Expenditures (State/Federal)" includes federal match dollars (the Federal Medical Assistance Percentage (FMAP)), as provided by APD.

ISF's preliminary analysis utilized data gathered from legislative documents. Future deliverables will include data provided by the Agency as well as data calculated from the algorithm. By utilizing Agency data over a longer time period (FY 2013-14 to 2024-2025), ISF will also be able to look at the iBudget program performance since its inception, identifying the effects of fiscal and statutory changes as well as exogenous shocks (e.g., COVID) and isolate their effects from those of the algorithm.

Figure 5: Total Adjusted GAA vs Expenditures displays five years of Total Adjusted Expenditures (FY18-19 through FY22-23) to better understand performance, volatility, and the relationship between spending and available funding.

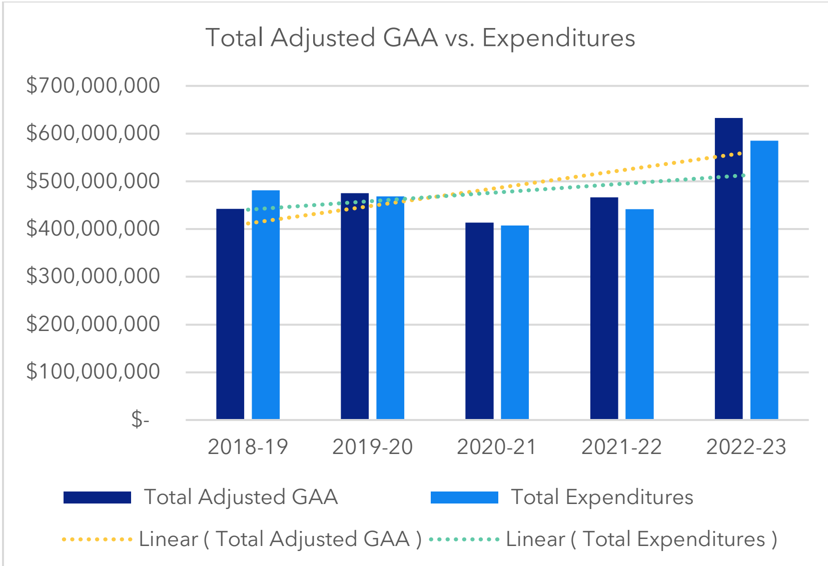

Figure 5: Total Adjusted GAA vs Expenditures

From FY18-19 to FY22-23, the iBudget system budget moved from a deficit of nearly $40 million to a surplus of more than $47 million. This stems from supplemental appropriations in FY18-19 and FY19-20 received by APD for $121.8 million in General Revenue to cover existing deficits. No additional appropriations were necessary through FY22-23. Since FY20-21, the surplus increased by more than $40 million, while expenditures decreased in FY19-20 and FY20-21. In FY21-22, expenditure began to increase, and in FY22-23, expenditure growth outpaced GAA growth for the first time in the analysis period. Despite this, both the total number of clients served and those in pre-enrollment have seen limited growth, remaining on relatively flat growth trajectories. It should be noted that the COVID-19 emergency may have influenced budget allocation increases and stagnant client enrollment, though additional research would be required to validate.

Figure 6: SANs Allocation and Clients Count displays five years of total SANs allocation and clients (FY18-19 through FY22-23) to better understand performance, volatility, and the relationship between SANs allocations and clients.

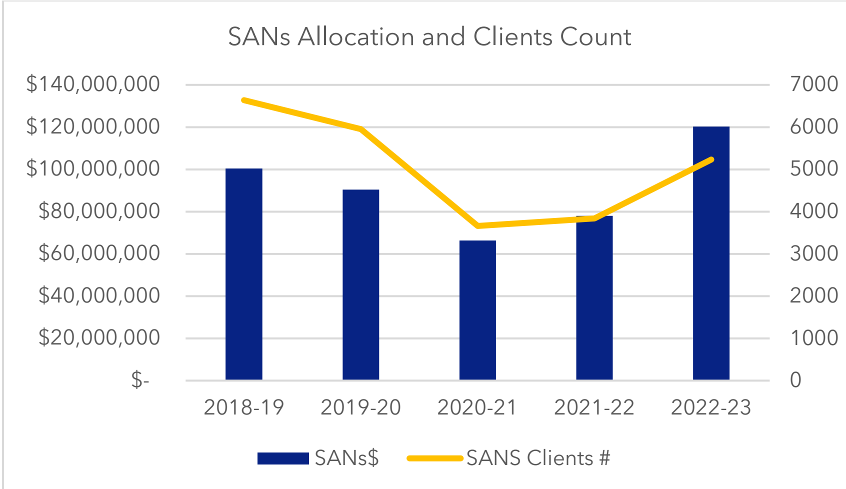

Figure 6: SANs Allocation and Clients Count

The total SAN allocation began to fall in FY19-20, before dramatically decreasing by 26.6% in FY20-21 and then stabilizing, surging, and surpassing FY18-19 allocation. SAN clients dropped even more dramatically than allocation from FY19-20 to FY20-21. The rates of recovery for appropriations have effectively outpaced the growth of SAN clients, which results in a continuing increase in allocation and spend potential per SAN client across all fiscal years assessed.

Concurrently, provider rates have increased substantially, increasing more significantly and rapidly than GAA appropriations for SANS or iBudget clients. Provider Rate Changes FY18-19 to FY22-23 details these increases over the five-year assessment period.

Table 3: Provider Rate Changes FY18-19 to FY22-23

Year	2018-19	2019-20	2020-21	2021-22	2022-23
Provider Rate Increases	$85,531,553	$114,250,847	$116,068,921	$116,068,921	$533,326,457

Provider rate costs increased more than ten times the average SANS allocation over five years. Similarly, the rate of provider cost increases has outpaced growth in funds appropriated, which from FY18-19 to FY22-23 increased by 35%.

The above analysis and supplementary research conducted by ISF suggest a complex operating environment that complicates the iBudget system's ability to provide efficient and effective service delivery. To fully assess the current algorithm, external factors and their impacts must be understood and controlled so that true algorithmic flaws, rather than system-level issues, can be identified as ISF continues its analysis of the iBudget system. Findings stemming from this analysis are organized by the following themes:

- **Operating Environment:** fiscal, organizational, and administrative conditions in which APD must operate the iBudget system
- **Legal and Regulatory Impacts:** statutory, regulatory, or judicial actions that have impacted the iBudget system's operations and may impact algorithm effectiveness

- **Performance and Demand:** ability to meet demand and achieve the desired outcomes of the iBudget system

Note: These are preliminary findings.

Operating Environment

Analysis revealed significant expenditure volatility, ranging from a $39.3 million deficit in FY18–19 to a $47.3 million surplus in FY22–23, with an average surplus of $9.3 million over the period. This volatility may impact the algorithm's ability to reliably predict and allocate funds across years. To accommodate the volatility, APD must rely on back-of-the-bill appropriations and the carry forward of funds, which may make the algorithm appear inefficient by showing unused funds that cannot be allocated or expended due to the operating environment.

Volatility may be attributed to changes in Medicaid financing, such as FMAP rate and multiplier changes, and economic conditions that impact the FMAP. Additionally, temporal challenges caused by Florida's fiscal year spanning two federal fiscal years may exacerbate volatility. Complexity in billing and payment may further this appearance of inefficiency in appropriations and expenditures. Providers of iBudget system services are paid by AHCA through the Florida Medicaid Management Information System, which has an interface with the iConnect system. Providers must navigate complex billing and documentation requirements, which can cause payment delays, creating the appearance of inefficiency.[9] Further, providers can bill up to one year after the date of service, further exacerbating the appearance of inefficiency.

Additionally, the person-centered service model, a federal HCBS requirement, creates additional uncertainty, impacting the ability to reliably predict expenditures and/or appropriations. The person-centered service model uses individualized planning and prioritizes individual choice in achieving desired outcomes.[10] As a result of individual choice, additional uncertainty is created.

Legal and Regulatory Impacts

The iBudget system is designed as a first-come, first-served, slot-limited program; it is not an entitlement program, but legal and regulatory changes have impacted the ability of the iBudget system to meet that design. Since the iBudget waiver's full implementation in 2013, multiple court cases, legal challenges, and regulatory changes have created financial uncertainty and driven additional funding needs. For example, in *Moreland v. APD*, 112. So.3d 152 *(2013)*, the First District Court of Appeal ruled that the agency did not provide sufficient notice to customers of the reduction in their allocations during the conversion to the iBudget system. This resulted in increased iBudgets of more than $150 million due to this ruling.[11]

[9] Florida Agency for Health Care Administration. (2023, May). Developmental disabilities individual budgeting waiver services coverage and limitations handbook. Florida Medicaid. https://ahca.myflorida.com/Medicaid/review/index.shtml
[10] Center for Medicare & Medicaid Services. (n.d.). Person-Centered Service Planning in HCBS: Requirements and Best Practices. https://www.medicaid.gov/medicaid/home-community-based-services/downloads/person-centrd-servc-plan-hcbs-req-best-pract.pdf.
[11] Agency for Persons with Disabilities. (2015, January 7). Update on litigation and regulations. Florida Senate Appropriations Subcommittee on Health and Human Services.
https://apd.myflorida.com/publications/legislative/docs/APD%20Litigation%20Review.pdf
See also:
Moreland v. Florida Agency for Persons with Disabilities (Case No. 1D12-1529) https://law.justia.com/cases/florida/first-district-court-of-appeal/2013/1d12-1529.html. See also Brandy v. Florida Agency for Persons with Disabilities (Case No. 4:17cv226-RH/CAS. https://law.justia.com/cases/federal/district-courts/florida/flndce/4:2017cv00226/92059/93/.

This demonstrates the dynamic legal and regulatory environment in which the iBudget system operates, the potential impacts such changes have on the system, and highlights the need for adaptability in the system, as well as in the algorithm.

Performance and Demand

The iBudget system was often unable to meet the demand of both enrollees and the pre-enrollment, as demonstrated by prior deficits, increased appropriations, and lagging enrollment growth despite deficit-spending appropriated by the legislature, resulting in significant deficit spending. ISF considered data from 2018 to 2022, which showed program enrollment increased by 1.37% while pre-enrollment increased by 4.38% - a rate more than three times higher. Despite the differential in these rates, the iBudget system experienced budget surpluses over 2019-2022, peaking at $24.8 million in FY21-22.

This suggests that performance inefficiencies may be the result of an outdated model that cannot effectively adapt to meet evolving needs, such as rising costs and changes in service delivery.

4.5 Accuracy and Reliability

Model 5b demonstrates the performance characteristics displayed in Table 4: Model 5b Statistical Accuracy Metrics after outlier removal.

Table 4: Model 5b Statistical Accuracy Metrics

2015 Metric	2015 Value	Meaning
R-squared	0.7998	R-squared is a figure used in statistics to measure how well a model explains the data. The 2015 R-squared of 0.7998 (the in-sample value) indicates that the model explains 79.98% of the variation in the data. The current R-squared value based on 2024 data is 0.2393 (in-sample).[12]
Adjusted R-squared	0.7996	Adjusted R-squared is similar to R-squared, adjusted for how many variables are in the model to prevent overfitting. The 2015 model still explained around 80% of the variation of the 2015 training data, even when accounting for its complexity.
Residual Standard Error	30.82	A representation of the average "distance" between a prediction and the actual value. A smaller number means more accurate predictions.
F-statistic	4,412	The F-statistic is used to measure the usefulness of the model. A high F-statistic, like the value calculated for Model5b, indicates that the model is statistically strong.
Degrees of Freedom	21 and 23,193	These numbers indicate how many variables are included in the model and the amount of data the model is trained on.
P-value	$p < 0.001$	A measure of statistical significance. A very small p-value indicates that the results of the model are real and not random.
SBC (Schwarz Bayesian Criterion)	159,394.3	A score used to compare models, where lower scores are better.

[12] Note that Tao and Niu reported in-sample R2, which uses training data, as well as with a squared root scale. ISF's current state assessment computed the R2 value based on out-of-sample, or test, data, and a real dollars scale.

While these metrics suggest strong statistical performance, there are opportunities to improve accuracy, including:

- Prediction Interval Coverage: Predictions for high expenditure clients, individuals with behavioral-focused needs, and transition-age populations fail to achieve nominal coverage rates.
- Systematic Bias: Patterns underestimate two questions regarding residential habilitation categories, and overestimate independent living and supported living settings, suggesting differential accuracy across service types.

The analysis of Model 5b's reliability identified the following areas for potential improvement:

- Temporal Stability: Model coefficients are based on FY13-14 data, and there is no mechanism for parameter updating or recalibration.
- Cross-Validation Performance: As a part of testing, Model 5b was subjected to cross-validation, wherein the model was tested against subsets of its training data. The cross-validation resulted in a lower R-squared value than the overall training performance and exhibited further performance degradation in folds containing complex or atypical cases.
- Internal Operations: QSI domains show strong performance around physical support needs; however, APD has an opportunity to strengthen data related to cognitive and social support requirements.

5 Conclusions and Next Steps

Three key areas where improvement opportunities were identified in the current state assessment are listed below.

- Methodological Approach: The statistical methods underlying Model 5b indicate technical competency within traditional regression frameworks.
- Data Input: APD has the opportunity to use supplementary data to strengthen the algorithm.
- Statistical Factors: The linear regression approach and the significance of some input variables could be strengthened based on recent data, which may afford expansion of independent variables.

Following the submission of this deliverable, ISF will review its contents with APD. ISF will review all feedback submitted by APD, make appropriate changes, and deliver a final version for APD approval.

The next deliverable for the APD iBudget Algorithm Study, Alternative Algorithms, will be developed via a structured and iterative process. The alternative algorithms will incorporate multiple approaches and be refined to the most viable options through rigorous testing. Each model will be evaluated using simulated representative populations to assess its capacity to incorporate additional waiver services and respond effectively to changing funding conditions.

6 Appendix

6.1 Definitions

Technical and mathematical terms used throughout this document are defined below.

- **Variables:** The specific pieces of information the algorithm uses to make decisions. Each variable represents a different factor. For example, in this case, the answers to QSI questions are each a distinct variable.
- **Coefficients:** The fixed numbers that tell the algorithm how much weight or importance to give to a variable. The larger the number, the higher the weight.
- **Interaction Terms:** Special parts of the formula that look at how two or more variables influence one another. Interaction terms are included to help the algorithm understand how the variables affect one another and impact the outcome.
- **Linear Regression:** A type of mathematical model commonly used in algorithms to find the relationships between different pieces of data. The model works by summing together the multiplication of variables and interaction terms with their coefficients.
- **Mathematical Fidelity:** High mathematical fidelity means the algorithm is accurate, consistent, and behaves as expected when processing data.
- **Outliers:** Pieces of input data that are far outside the range of expected values for similar data across the dataset.
- **Robustness:** The extent to which the algorithm works well even when the data is messy, unusual, or slightly wrong. A robust algorithm will give reliable results even with questionable data quality.
- **Edge Cases:** Unusual or rare situations that do not follow the typical pattern seen in the dataset.
- **Residual:** The distance (error) between a predicted value and the actual value.
- **Homoscedasticity:** The extent to which the error in a model is evenly spread out. In other words, a homoscedastic model will make similarly sized mistakes regardless of whether it's predicting something small or large. The opposite of homoscedasticity is heteroscedasticity.
- **Z-Score:** A statistical measure of distance that indicates how many standard deviations a datapoint is away from the average. In the case of a linear regression, the Z-score is the measure of distance between the actual result (the data point) and the predicted result (the average).
- **Standard Deviation:** A statistical measure that indicates the variation in a dataset. Specifically, it measures the average distance of datapoints from the mean. A low standard deviation means that the data is closely clustered around its mean.

6.2 Basics of Algorithms

Algorithms like Model 5b are mathematical formulas designed to ingest input data, then transform and combine that data through a series of logical operations into an output. Algorithms are used in a wide range of applications, from financial modeling to public policy decision-making. Algorithms with equivalent inputs can have vastly different outputs, depending on the transformations they apply. The key components of any algorithm include the following:

- Input Data: The raw data or information the algorithm receives. This could include numbers, categories, or other types of data relevant to the task at hand.

- Transformations: The set of instructions or formulas the algorithm applies to the input data to calculate its output. These can include operations like multiplying values by a coefficient or each other, replacing variables, or applying statistical models. These transformations will determine how the input is interpreted and processed.
- Output: The resultant figure or decision produced by the algorithm. This could be a score, classification, recommendation, or other actionable output.

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State of Florida

Alternative Algorithms

Florida Agency for Persons with Disabilities

2025 iBudget Algorithm Study

October 24, 2025

Deliverable 3 – Alternative Algorithms (Version 2)

Table of Contents

Table of Tables

Table of Equations

Acronyms

Acronym	Definition
ADL	Activities of Daily Living
APD	Agency for Persons with Disabilities
CI	Confidence Interval, or when used with Bayesian statistics, the Credible Interval
CMS	Centers for Medicare and Medicaid Services
D	Deliverable
DV	Dependent Variable
FAC	Florida Administrative Code
FS	Florida Statute
FY	Fiscal Year
HB	House Bill
HCBS	Home and Community-Based Services

IV	Independent Variable
MI	Mutual Information
ML	Machine Learning
TCO	Total Cost of Operation
QSI	Questionnaire for Situational Information
WLS	Weighted Least Squares

Glossary

Term	Definition
Bayes Theorem	Calculates the conditional probability of event A, given that event B has already occurred. This uses prior knowledge to provide more precise estimates.
Bayesian Linear Regression	An extension of linear regression based on Bayes' Theorem, which uses prior or historical data to inform data contributing to the model (i.e., the posterior probability). It accomplishes this by producing probability distributions, calculating a likelihood function, and updating the posterior distribution to reflect model results.
Central Limit Theory	States that the larger the sampling population, the more normally the data will be distributed
Cook's Distance	A measure that shows how much a single data point influences a regression model. A high distance means the data point might be distorting the results.
Decile	A way to split data into ten equal parts. Each decile represents 10% of the sorted data.
Deep Learning Neural Network	A technique that is nested within artificial intelligence and machine learning. By using a combination of layered and connected nodes, information is passed across to better identify patterns.
Git-based version control	Uses a distributed version control system (i.e., GitHub) to record all changes and improve replicability.
Heteroscedasticity	Refers to data with variability that is unequal (e.g., scattered across a set of predictor variables modeled by a linear line). For regression models, the data should be homoscedastic, so methods to correct heteroscedasticity are sometimes employed.
Homoscedasticity	Refers to data that has a constant variance of errors and is typically required for regression analyses.
Huber Loss function	Combines two types of loss functions (MSE and MAE) to help account for bias in regression models.
Kolmogorov-Smirnov	This is a non-parametric test which assesses whether two samples are significantly different from each other and is often used for checking uniformity in a random set of numbers.
Leverage Analysis	Process of identifying data points that have a lot of influence on a model because of how far they are from the average, in terms of input values.

Term	Definition
Likelihood Function	Similar to a CI, this function indicates how likely data is to occur for a value of the parameter. Essentially, explaining how well the model explains the data using the parameter.
Log-Normal Regression	An extension of linear regression which accounts for predictor data that is positively, or right, skewed by applying a log-transformation.
Mean Absolute Error (MAE)	MAE measures the average absolute distance between predicted and actual values (error). MAE treats all errors equally and is more robust to outliers than RMSE.
Mean Absolute Percentage Error (MAPE)	MAPE expresses MAE accuracy as a percentage by comparing absolute error to the actual value.
Multiple-linear Regression	This modeling approach is a derivative of the classic slope-intercept formula (y=mx+b), used for modeling a straight line. The difference with regression, though, is that it is attempting to identify the line that best fits the data (e.g., drawing a fitted line through a scatterplot wherein the datapoints are evenly distributed along the line, and their distance from the line is minimized). A multiple-linear regression is different from a simple or general linear regression in that it can incorporate multiple predictors in the same model.
Multicollinearity	Refers to data that is highly correlated, often referring to independent variables in a regression model.
Ordinary Least Squares	A method for finding the best-fitting line through data by minimizing the total squared differences between predicted results and actual values.
Precision	A measurement to assess how close each measurement is to each other. Assesses the random error, which is lower when precision is high.
Posterior Probability	Also known as the posterior distribution is the result of the prior distribution and the likelihood function. This indicates the updated knowledge about the data.
Prior Distribution	This indicates the initial beliefs about the data (prior to seeing the data) and develops parameters to account for the uncertainty. These can be developed using either informative priors (include strong knowledge or expert opinions) or non-informative priors (uses minimal assumptions, and best when little is known about the expectations of the data).
Quantile Regression	This is an extension of linear regression, but instead of using OLS and computing a conditional mean, it instead estimates quantiles of the dependent variable.
R-Squared (R^2)	Measure of the model's ability to accurately explain the variance within the data. A score closer to 1 means increased accuracy.
Random Forest	A method that makes predictions by combining the results of many simple decision trees, each looking at different parts of the data. By averaging their outputs, it creates a more accurate and stable prediction than any single tree alone.
Ridge Regression (L2 Regularization)	An extension of linear regression designed to address problems with multicollinearity. This is addressed by adding a regularizing term to the OLS. This de-emphasizes large coefficients and lowers the overall variance.

Term	Definition
Root Mean Squared Error (RMSE)	RMSE measures the square root of the average squared distance between predictions and their actual value (also known as error). As a result, RMSE penalizes larger errors more heavily. A lower RMSE means a more accurate model.
Sensitivity (True Positive Rate)	Known both as sensitivity and true positive rate, indicates the likelihood of a test correctly identifying positive cases.
Specificity (True Negative Rate)	Known both as specificity and true negative rate, indicates the likelihood of a test correctly identifying negative cases.
Studentized Residuals	These are residual errors standardized over the standard deviation of the dataset.
Sum of Squared Errors (SSE)	SSE takes the distance from each point to the line, summing the values and then squaring.
Weighted Least Squares (WLS)	This is a type of linear regression that applies weights to each data point, often to address heteroscedasticity. OLS regression treats each data point equally, WLS applies a weighting strategy and works to minimize the weighted (w_i) sum of squared residuals.

Revision History

Version	Date	Author	Notes
V2	10/24/2025	ISF	D3 for APD Review

1 Executive Summary

The Home and Community-Based Services (HCBS) iBudget system is part of Florida's Medicaid waiver system, which provides individuals with developmental disabilities the opportunity to receive care and support in their homes and communities. The iBudget uses an algorithm based on age, living setting, and information from the Questionnaire for Situational Information (QSI), along with a supplemental assessment as needed, to allocate individualized budgets that reflect each person's unique needs. The Agency for Persons with Disabilities (APD) administers the iBudget, currently serving over 36,000 people, with over 20,000 in pre-enrollment categories.

ISF was engaged to conduct a comprehensive analysis of the statistical and mathematical foundations of Model 5b, the algorithm currently used by APD to determine individual iBudgets, as well as recommend alternatives to increase its effectiveness. An analysis of the existing iBudget algorithm was documented in the Current Algorithm Assessment, deliverable (D) 2 of the iBudget Algorithm Study, providing a foundation for identifying both strengths and limitations of the existing iBudget algorithm approach. The analysis indicated that there were opportunities for improvement. Building on the insights from that analysis, ISF systematically developed a series of alternative algorithmic models, carefully adjusting key parameters and methodological assumptions to explore potential improvements (documented within this deliverable).

Alternative algorithms provide options for APD to examine different approaches to serving Florida's iBudget system population.

Real historical data (September 1, 2023 – August 31, 2024) was run through seven alternative algorithm models to evaluate their outputs. Originally, ten alternative algorithms were developed and assessed. However, three of the models (7, 8, and 10) were excluded as they did not produce single budget allocations as required for iBudget clients. The seven algorithms represent advanced mathematical approaches to budget allocation determinations, as displayed in Figure 1: Alternative Algorithm Descriptions. Each of the seven alternative algorithm models was documented and assessed with the following categories:

1. Accuracy and Reliability
2. Sensitivity to Outliers and Missing Data
3. Assessment of Robustness
4. Implementation Feasibility
5. Complexity, Cost, and Regulatory Alignment
6. Feasibility of Changes

Note: *The data referenced in this report is currently in a beta 1.0 state as of 10/23/25. There may be a slight variance in the data between this D3 V3 document, the scientific report, and the final report due to a re-run of data.*

Furthermore, this information reflects ISF's professional assessment and is provided for discussion purposes. All findings and recommendations are subject to confirmation and approval by APD.

Algorithm Model	Description
Tier 1: Direct Replacement Candidates	
Model 1: **Re-estimated Linear Regression**	Maintains the exact Model 5b structure while updating coefficients with current data. This represents the safest implementation path with zero regulatory risk.
Model 2: **Generalized Linear Model w/ Gamma Distribution**	Replaces square root transformation with a log-link function, which is a better fit for expenditure data. The underlying math removes the need for outlier exclusion.
Model 3: **Robust Linear Regression**	Maintains the structure of Model 5b while automatically handling outliers through an iterative process of coefficient determination.
Tier 2: Conditional Replacement Candidates	
Model 4: **Weighted Least Squares**	Leverages an approach that gives more influence to trustworthy datapoints while reducing the influence of outliers and noise.
Model 5: **Ridge Regression**	Adds penalization to variables with large coefficients, allowing for a more stable and consistent predictions.
Model 6: **Log-Normal Regression**	Models the data according to a log-normal distribution that more naturally fits expenditure data.
Tier 3: Advanced Methods Requiring Framework Challenges	
Model 9: **Random Forest**	Leverages decision trees, flowchart-like structures, that split data based on feature values to make predictions. The model averages the results of those decision trees to arrive at its predictions.

Figure 1: Alternative Algorithm Descriptions

2 Background

Through the HCBS Medicaid waiver, the United States Centers for Medicare & Medicaid Services (CMS) allows certain federal Medicaid rules to be waived. In Florida, the Agency for Health Care Administration (AHCA) administers the Medicaid program, and partners with APD to deliver the HCBS waiver program to eligible individuals. APD manages the waiver program through the iBudget system, thereby ensuring clients receive medically necessary support and services that promote independent living.

Each client's iBudget amount is calculated using the allocation algorithm in Rule 65G-4.0214, Florida Administrative Code (FAC), based on QSI factors, plus any significant additional needs identified in individual reviews. Based on the current state assessment of the allocation algorithm, Model 5b, established in 2015, there are opportunities for improvement. ISF found that Model 5b, as tested, is functioning as predicted for iBudget clients. However, there have been significant strides in technology, including artificial intelligence (AI) and advanced data analytics that support the processing of large datasets, and can enhance how the algorithm functions over time. Furthermore, there have been changes in appropriations and policy in the last 10 years that the algorithm can better adjust to.

In the present landscape of computational science, advanced mathematical techniques have significantly enhanced the accuracy, predictability, and reliability of complex systems modeling. These methodologies encompass innovative strategies, intelligent algorithms, and agent-based models, which collectively facilitate more precise and dependable outcomes. By leveraging these advanced techniques, ISF developed a diverse suite of alternative algorithms, each specifically designed to tackle distinct challenges and enhance the accuracy, efficiency, and overall performance of the iBudget algorithm. However, beyond the advanced technical landscape, additional barriers exist in the form of state and federal regulations that the program must follow. Together, these technical complexities and regulatory constraints highlight the challenging landscape.

To date, there are more than 36,000 individuals enrolled in the iBudget system, with a pre-enrollment list of over 20,000 people. Implementing a more robust model can address the challenge of fully utilizing appropriated funds, reducing the risk of unspent allocations, and reversion. At the same time, it ensures that individuals receive the funding necessary to meet their unique needs, promoting greater independence and self-sufficiency.

This deliverable, D3 Alternative Algorithms, includes multiple alternative algorithms, including multiple linear regression models using QSI scores, to determine individual budgets for HCBS. Each algorithm prioritized a person-centered approach and was tested for accuracy, reliability, and robustness, including sensitivity to outliers and missing data. ISF also assessed feasibility, considering compatibility with APD systems, data and training requirements, implementation cost, regulatory alignment, and adaptability to increases in appropriations.

3 Approach

The approach to this analysis included identifying and assessing seven alternative algorithm methods across six categories, supporting a comprehensive evaluation of impact and feasibility. The approach to this analysis included identifying and assessing alternative algorithm methods across six categories, supporting a comprehensive evaluation of impact and feasibility. The categories of the assessment included:

- Accuracy and Reliability
- Sensitivity to Outliers and Missing Data
- Assessment of Robustness
- Implementation Feasibility
- Complexity, Cost, and Regulatory Alignment
- Feasibility of Changes

The seven algorithm methods assessed were chosen based on value-traits such as statistical sophistication, implementation complexity, and regulatory compliance (including the removal of three noncompliant alternatives). As a baseline, ISF maintained the understanding that any replacement algorithm must meet or exceed the performance of the current algorithm while providing deterministic, single-point budget allocations that can withstand appeals processes.

3.1 Model Implementation and Testing

The Current Algorithm Assessment (D2) provided a foundation for identifying both strengths and limitations of the existing approach, which uses Model 5b, designed based on 2013-2014 data. Building on these insights, ISF systematically developed a series of alternative algorithmic models, as presented in this deliverable, carefully adjusting for key parameters and methodological assumptions to explore potential improvements. The assessments of these alternative algorithmic models included four critical dimensions for evaluation:

- Fit to recent expenditure data
- Identification and refinement of variables
- Development of outlier management methods
- Evaluation of accuracy and reliability

Real historical data (September 1, 2023 – August 31, 2024) was run through seven alternative models to evaluate their outputs, facilitating an assessment of accuracy, reliability, and other requirements. The outputs were then fully assessed to determine the impact and feasibility of each algorithm, which will support the recommendation of an algorithm model to be presented in D4, Recommended Algorithm. Models 1-6 present variations of linear regression algorithms, as required in HB 1103, with varying inputs, weights, and formulas. Model 9 demonstrates a different statistical approach for consideration, ensemble, decision-tree based machine learning.

Note: *The algorithm implementations referenced in this report are currently in a beta state. Although the seven algorithms have been fully developed, their outputs should be interpreted accordingly. Throughout the study, the algorithms will be systematically refined, validated, and updated to ensure accuracy and reliability.*

3.2 Data Preparation and Feature Selection

The alternative algorithms were trained, tested, and validated using client data from APD's database, spanning 3 fiscal years: 2022-2023, 2023– 2024, and 2024-2025. For the purpose of this analysis, each

FY spanned September 1 through August 31 based on how payments are made within and outside of the state FY (July 1 – June 30). Every client record was considered individually whenever an allocation was received (i.e., client year).

Criteria used to disqualify data points included:

- **Late entry/Early Exit:** Clients who entered or left the system more than 30 days before/after the FY end/start
- **Missing QSI Assessment:** No QSI assessment linked to the given FY
- **Insufficient Service Days:** Fewer than 30 service days within the given FY
- **Zero Cost:** Records with no annual expenditure
- **Zero Variance:** Features with zero variance within a fiscal year

To select which features (datapoints) to use for model training/testing/ validation, ISF developed a threshold-based approach:

- **Mutual Information Threshold:** Features with Mutual Information (MI) ≥ 0.03 were considered for inclusion
- **Correlation Filtering:** Among feature pairs with an association threshold $\tau > 0.9$, only the feature with the higher MI was retained
- **Temporal Consistency:** Appearance in top-20 rankings across multiple years
- **Missingness Profile:** Features with relatively low missingness (e.g., <10% post-filtering) were preferred, all else equal.

Additional features were selected based on regulatory and clinical considerations:

- **Mandatory Inclusions:** Age, gender, primary diagnosis, and county were retained regardless of MI scores to satisfy regulatory requirements and enable demographic analyses
- **Clinical Subscales:** QSI subscales (Functional: Q14-24, Behavioral: Q25-30, Physical: Q32-50) were included as complete sets to preserve psychometric properties
- **Service Context:** Living setting and residence type variables were prioritized given their policy relevance and strong predictive power

54 independent variables were selected for predictive use. Table 1: Selected Feature Set reflects the independent variables selected. Please note that there are 54 total independent variables; the inclusion of categorical variables that were one-hot encoded resulted in a larger set of actual input features.

Table 1: Selected Feature Set

Variable	Label
X_1	LivingSetting
X_2	LOSRI
X_3	OLEVEL
X_4	BLEVEL
X_5	FLEVEL

Variable	Label
X_6	PLEVEL
X_7	Age
X_8	AgeGroup
X_9	County
X_{10}	BSum
X_{11}	FSum
X_{12}	PSum
X_{13}	FHFSum
X_{14}	SLFSum
X_{15}	SLBSum
X_{16}	SupportedLiving_x_LOSRI
X_{17}	Age_X_Bum
X_{18} - X_{54}	QSI Q14-50

Living Setting: The Living setting variable is encoded through five categorical indicators representing Independent Living/Supported Living (ILSL), three levels of residential habilitation (RH1, RH2, RH3), and Family Housing (FH), with a fourth residential habilitation level (RH4) serving as the reference category.

County: Geographic variation in service costs and availability is captured through county-level indicators, though we note that Model 9 (Random Forest) excludes these geographic features as their inclusion degraded performance in tree-based algorithms.

Age, Age Group: The foundation of our feature set consists of demographic characteristics and standardized assessment scores. Age enters the model in two forms: as a continuous variable to capture linear age effects, and through three binary age group indicators (under 21, ages 21-30, and over 30) to model potential non-linear relationships across life stages. These age representations allow the model to flexibly adapt to both gradual developmental changes and discrete transitions between age-related service patterns.

Standardized Support Level Assessments: The standardized support level assessments across multiple domains are central to the feature set. The Overall Support Level (olevel) provides a holistic measure, while domain-specific levels capture needs in behavioral (blevel), functional (flevel), and physical (plevel) areas. These are complemented by summary scores in each domain (bsum, fsum, psum) that aggregate the detailed item-level assessments. The Level of Support and Risk Inventory (LOSRI) provides an additional comprehensive measure of support intensity and associated risks.

Interaction Terms: Recognizing that support needs often arise from combinations of factors rather than independent effects, we incorporated five theoretically motivated interaction terms. The Family Housing-Functional Summary interaction (FH_x_FSum) captures the differential impact of functional limitations in family settings compared to other residential arrangements. Two interactions involving Supported Living settings (defined as RH1 through RH4) reflect the hypothesis that behavioral and functional needs may manifest differently in these environments: Supported Living-Functional Summary (SL_x_FSum) and Supported Living-Behavioral Summary (SL_x_BSum). The Supported Living-LOSRI interaction (SupportedLiving_x_LOSRI) further explores how overall support intensity scales with residential setting. Finally, the Age-Behavioral Summary interaction (Age_x_BSum, scaled by a factor of 1/100 for numerical stability) allows behavioral support needs to have age-varying effects.

QSI Items 14-51: The Questionnaire for Situational Information (QSI) contributes substantially to the feature set. Initial mutual information analysis identified items 26, 36, 27, 20, 21, 23, 30, and 25 as having the strongest individual predictive power. However, given that most QSI items demonstrated meaningful information content (mutual information above 0.05), we ultimately included the complete set of items 14 through 50, representing 37 distinct situational indicators. This decision reflected the empirical finding that comprehensive QSI inclusion marginally improved model performance while maintaining clinical interpretability, as each item corresponds to a specific assessed need or circumstance.

After arriving on this feature set, the ISF team executed a verification process to confirm correctness and reproducibility, including:

- **Cohort Eligibility checks by FY:** Quality flags were applied, and strictly positive cost was enforced. For each FY, ISF confirmed that no ineligible records remained in the final cohorts.
- **Mutual Information configuration audit:** Adjusted MI is computed with a discrete-feature mask and a permutation baseline. ISF confirmed that these settings are fixed in the code path and echoed in the run log.
- **Stability indicators**: Temporal consistency is summarized by the counts exported to macros:
    - Features in all years' top-10: 8
    - Features in most years' top-10: 9

  These indicators provide a lightweight stability check without asserting a specific selection cutoff.
- **Redundancy pruning and VIF actions:** Pairware pruning and iterative VIF removal are executed prior to reporting. The pipeline logs list any features dropped by these steps, which are reflected in the final MI rankings.
- **Diagnostic artifacts present and renderable:** For each FY, the following plots are generated and compiled:
    - Spearman heatmap (continuous)
    - Cramer's *V* heatmap
    - Correlation ratio (mixed)
    - Pairplot (top continuous + *Y*)
- **Reproducibility controls:** All stochastic operations use a fixed random seed (42).
- **Clinical Face Validity:** Domain experts from APD validated that selected features represent clinically meaningful cost drivers.

3.3 Impact and Feasibility

To evaluate the alternative solutions, each alternative algorithm was assessed across six key categories for impact or feasibility, described below.

The following were tested for impact:

- Accuracy and Reliability: How correct the algorithm's outputs are and how consistently it produces the same results.
- Robustness: How well the algorithm performs under varying conditions or changes in input.
- Sensitivity to Outliers and Missing Data: How much does unusual or missing data affect the algorithm's performance.

The following were tested for feasibility:

- Implementation: How easy it is to put the algorithm into practice.
- Complexity, Cost, Regulatory Alignment: How complicated or expensive it is, and how well it meets rules and regulations. All cost estimates are preliminary figures based on ISF's experience and knowledge, and do not include costs related to communications and materials.
- Changes: How feasible it is to modify or update the algorithm as needed.

Alternative Algorithms Overview .

Table 2: Overview of Alternative Algorithms provides an overview of the tiers and the alternative algorithms. Each was evaluated on accuracy, reliability, robustness, sensitivity to data issues, feasibility of implementation, regulatory alignment, and overall practicality of the change for APD's implementation. Summaries of each algorithm, organized by tier, are provided below. *Each model's accuracy and performance were benchmarked against ISF's assessment of the current algorithm, Model 5b, which produced an R^2 of 0.2528 when replicated and tested using FY 24-25 data.*

Table 2: Overview of Alternative Algorithms

Model Name	Section Reference Link	Model Description
Model 1: Re-estimated Linear Regression	4 Model 1- Updated Model 5b	Maintains the exact Model 5b structure while updating coefficients with current data. This represents the safest implementation path with little regulatory risk. The primary advantage is current state regulatory compliance with minimal stakeholder disruption. However, it maintains the 9.40% outlier exclusion requirement. Model 1 improves predictive accuracy by ~95% when compared to the current algorithm.
Model 2: Generalized Linear Model with Gamma Distribution	5 Model 2 – Generalized Linear Model	Replaces square root transformation with a log-link function, naturally accommodating right-skewed expenditure data. This approach eliminates back-transformation bias and achieves a ~69%% increase in accuracy compared to the current algorithm. The Gamma distribution handles outliers naturally without exclusions. Implementation requires six to 12 months, including regulatory rule updates to specify the link function. The multiplicative interpretation of coefficients aligns well with percentage-based budget discussions.

Model Name	Section Reference Link	Model Description
Model 3: Robust Linear Regression	6 Model 3 – Robust Linear Regression	Uses Huber M-Estimators to represent the optimal balance between innovation and compliance. It includes all clients through automatic outlier downweighing rather than exclusion. Each client receives a weight between 0 and 1, indicating data quality. Predictive accuracy increased by ~97% compared to the current algorithm. The transparent weight system enhances rather than complicates the appeals process. Implementation requires six months with moderate training requirements.
Model 4: Weighted Least Squares	7 Model 4 – Weighted Least Squares Regression with Variance-Based Weighting	Addresses heteroscedasticity through variance-based weighting, achieving ~105% higher predictive accuracy compared to the current algorithm. However, significant equity concerns arise as weights could create systematic bias across demographic groups. Implementation requires 12-18 months with extensive fairness testing and continuous monitoring. The approach offers superior efficiency for stable cases but may disadvantage high-need iBudget service waiver clients with variable costs.
Model 5: Ridge Regression	8 Model 5 – Ridge Regression	Applies L2 regularization to handle multicollinearity among QSI variables. While offering the highest stability, the shrinkage concept proves difficult to explain to non-technical audiences. Predictive accuracy increases ~106% when compared to the current algorithm,% and generalization improves. The requirement to retain all predictors aligns with current regulations, though penalty parameter justification remains challenging.

Model Name	Section Reference Link	Model Description
Model 6: Log-Normal Regression	9 Model 6 – Log-Normal Regression	Uses natural log transformation, which Box-Cox analysis indicates as superior to the square-root. The model increases predictive accuracy by ~82% when compared to the current algorithm. Regulatory approval requires definitive statistical evidence of superiority over the current transformation. Retransformation bias must be carefully managed using smearing estimators or parametric corrections.
Model 9: Random Forest	10 – Random Forest	Averages the predictions of 500 decision trees to arrive at a final prediction. This model has the benefit of not assuming a distribution on the data, which allows it to better observe and account for interactions and nonlinearities in the data. The model is fully compliant with all salient Florida and federal regulations. It achieves the highest improvement in predictive accuracy over the current algorithm at ~160%.

4 Model 1- Updated Model 5b

Description: Model 1 is a linear regression model that replicates the exact mathematical formula used in the current algorithm (Model 5b), but updates the factors and inputs used to make the calculations for individual allocation amounts from what was originally set in 2013 – 2014.

Results: This model improves predictive accuracy by ~95% (Test $R^2 = 0.4932$) when compared to the current algorithm (Model 5b).

Additional Factors: Model 1 is not appropriately fitted with the distribution of iBudget data. This partially explains why 9.40% of cases were excluded in the initial development of the model. This indicates an increased likelihood of cases that will be found to be ineligible for funding, or an increased number requiring extra specialized reviews. There are also areas for improvement, such as updating methodological best practices (the original model was developed in 2015, and there have been significant mathematical advances since then).

The algorithm has limited implementation risk, is fully compliant with relevant regulations, uses a proven methodology, and is fully interpretable and transparent.

4.1.1 Algorithm

To calculate the actual iBudget services amount a client will receive, the results of the multiple linear regression equation are squared to support interpretability (i.e., yield a monetary outcome). The iBudget allocation calculation for this model is displayed in Equation 1: Model 1 iBudget Allocation Calculation.

Equation 1: Model 1 iBudget Allocation Calculation

$$Budget_i = \left(\hat{\beta}_0 + \sum_{j=1}^{54} \hat{\beta}_j X_{ij}\right)^2$$

For additional information and analysis related to Model 1, see Appendix Section 12.1, Model 1 Additional Details.

4.1.2 Model 1 Implementation Feasibility and Impact

The results of Model 1's implementation feasibility study are provided in Table 3: Model 1 Implementation Feasibility Results.

Table 3: Model 1 Implementation Feasibility Results

Categories	Model 1
Impact	
Accuracy and Reliability	Model 1 improves the predictive accuracy by ~90% (Test R^2 = 0.4932) compared to the baseline (Model 5b). The model is consistent and reliable but appears to provide more accurate predictions for individuals with high needs compared to those with lower needs.
Robustness	Model 1 is a robust model that displays little variance in accuracy across different subgroups, including age, gender, race, and geography.
Sensitivity to Outliers and Missing Data	Following the approach of the current algorithm, Model 1 removes 9.40% of the dataset in accordance with the residual detection methodology. The algorithm does not appear to be sensitive to missing data.
Feasibility	
Implementation	Due to the algorithm's similarity to the existing model, implementation of Model 1 is estimated to be a two-week process, including a pilot and a two-hour training exercise. There is expected to be a limited impact on service providers.
Complexity, Cost, Regulatory Alignment	The total three-year cost of ownership (TCO) of Model 1 is preliminarily estimated at $80,000.00. An estimated $35,000.00 of that amount would be directly related to development and implementation. *See the appendix for additional details on preliminary cost estimates.*
Changes	The model supports updates, changes, and audits through Git version control, automatic reporting, and performance drift detection.

5 Model 2 – Generalized Linear Model with Gamma Distribution

Description: Model 2 is similar in formulation to Model 1 but replaces the square root transformation (previously used to improve interpretability) with a better aligned approach for interpreting expenditure data that is positively skewed to the right. This is done by using the logarithmic scale. The model continues to make predictions based on the same set of QSI items as both the current algorithm and Model 1.

Results: Model 2 has ~69% (Test $R^2 = 0.4261$) higher predictive accuracy than the existing algorithm (Model 5).

Additional Factors: Model 2 has statistical properties that are more in line with expenditure data than a traditional regression approach and does not require outlier exclusion. However, it is also more complex than simple linear regression, requiring statistical expertise to maintain, is less intuitive to interpret, and requires updates to existing regulatory rules.

5.1.1 Algorithm

To calculate the actual iBudget services amount a client will receive, the results of the generalized linear model equation are exponentiated to support interpretability (i.e., yielding a monetary outcome). The budget allocation calculation for this model is displayed in Equation 2: Model 2 iBudget Allocation Calculation.

Equation 2: Model 2 iBudget Allocation Calculation

$$Budget_i = \exp\left(\hat{\beta}_0 + \sum_{j=1}^{54} \hat{\beta}_j X_{ij}\right)$$

For additional information and analysis related to Model 2, see Appendix Section 12.2, Model 2 Additional Details.

5.1.2 Model 2 Implementation Feasibility and Impact

The results of Model 2's implementation feasibility study are provided in Table 3: Model 2 Implementation Feasibility Results.

Table 4: Model 2 Implementation Feasibility Results

Categories	Model 2
Impact	
Accuracy and Reliability	Model results in ~69% (Test R^2 = 0.4261) increase in predictive accuracy when compared to the baseline.
Sensitivity to Outliers and Missing Data	Due to its formulation, Model 2 does not require outlier removal to achieve strong performance.
Feasibility	
Implementation	Model 2 requires a six-month implementation involving an eight-hour training workshop and a 1,000-client pilot test. Client parallel run is recommended.
Complexity, Cost, Regulatory Alignment	Estimated TCO of $220,000.00. $130,000.00 of that amount is directly related to development and implementation. Model 2 appears to be aligned with regulatory requirements pending a rule update to 65G-4.0214, FAC. *See the appendix for additional details on preliminary cost estimates.*
Changes	Model 2 supports updates and changes through automated reporting and drift detection, though the process may require a resource with additional statistical expertise.

6 Model 3 – Robust Linear Regression

Description: Model 3 is a robust linear regression model that maintains the existing algorithm's structure, but accounts for the outliers (i.e., 9.40% were excluded in the original model development). The core model still uses a square root transformation for interpretability, but incorporates a Huber Loss function to automatically handle outliers through a process of iterative coefficient determination.

Results: Model 3 has ~97% (Test R^2 = 0.4979) higher predictive accuracy than the existing algorithm (Model 5b).

Additional Factors: The algorithm no longer removes the outliers via an exclusion process (as required by the original algorithm), has enhanced explainability, and results in improved fairness and equity in outcomes. However, it also increases the computational complexity of the model and requires statistical expertise to interpret and communicate.

6.1.1 Algorithm

To calculate the actual iBudget services amount a client will receive, the results of the robust linear regression are squared to support interpretability (i.e., yielding a monetary outcome). The budget allocation calculation for this model is displayed in Equation 3: Model 3 iBudget Allocation Calculation.

Equation 3: Model 3 iBudget Allocation Calculation

$$Budget_i = \left(\hat{\beta}_0^R + \sum_{j=1}^{54} \hat{\beta}_j^R X_{ij}\right)^2$$

For additional information and analysis related to Model 3, see Appendix Section 12.3, Model 3 Additional Details.

6.1.2 Model 3 Implementation Feasibility and Feedback

The results of Model 3's implementation feasibility study are provided in Table 5: Model 3 Implementation Feasibility Results.

Table 5: Model 3 Implementation Feasibility Results

Categories	Model 3
Impact	
Accuracy, Reliability, and Robustness	Model results in ~97% (Test R^2 = 0.4979) higher predictive accuracy than the baseline.
Sensitivity to Outliers and Missing Data	The usage of an iterative weighting process makes the model very robust to outliers, with no exclusion required.
Feasibility	
Implementation	While still feasible, Model 3 would require modifications to the existing APD database and technical stack. The implementation would likely take six months and require multiple training workshops and a pilot test.
Complexity, Cost, Regulatory Alignment	The preliminary estimated three-year cost of $195,000.00, $100,000.00 of which is directly related to development and implementation. The model is fully compliant with existing regulations pending a rule modification around weight documentation. *See the appendix for additional details on preliminary cost estimates.*
Changes	Model 3 was designed to automatically adjust dynamically to changes in the data and can be adjusted easily based on policy changes. This process may require a resource with additional statistical expertise.

7 Model 4 – Weighted Least Squares Regression with Variance-Based Weighting

Description: Model 4 Weighted Least Squares (WLS) linear regression uses an approach that gives more attention to higher quality data points, while reducing the influence of outliers, helping the model make more accurate predictions. This is an extension of the regular linear regression that uses ordinary least squares, applying similar techniques except for how residuals are handled and not requiring outlier exclusion.

Results: Model 4 has ~105% (Test $R^2 = 0.5171$) higher predictive accuracy than the existing algorithm (Model 5b).

Additional Factors: Model 4 is very efficient for stable cases, offers improved precision where it matters most, and addresses the data's Heteroscedasticity while maintaining interpretability. However, it also poses a high risk of discriminatory impact, requires complex implementation and maintenance procedures, and poses potential legal vulnerabilities.

7.1.1 Algorithm

To calculate the actual iBudget services amount a client will receive, the results of the WLS linear regression are squared to support interpretability (i.e., yielding a monetary outcome). The budget allocation calculation for this model is displayed in Equation 4: Model 4 iBudget Allocation Calculation.

Equation 4: Model 4 iBudget Allocation Calculation

$$Budget_i = \left(\hat{\beta}_0^{WLS} + \sum_{j=1}^{54} \hat{\beta}_j^{WLS} X_{ij} \right)^2$$

For additional information and analysis related to Model 4, see Appendix Section 12.4, Model 4 Additional Details.

7.1.2 Model 4 Implementation Feasibility and Impact

The results of Model 4's implementation feasibility study are provided in Table 6: Model 4 Implementation Feasibility Results.

Table 6: Model 4 Implementation Feasibility Results

Categories	Model 4
Impact	
Accuracy, Reliability, and Robustness	Model results in ~105% (Test R^2 = 0.5171) higher predictive accuracy than the baseline.
Sensitivity to Outliers and Missing Data	WLS methodology allows the model to forego outlier exclusion for improved coverage.
Feasibility	
Implementation	Implementation requires comprehensive documentation and training, as well as equity monitoring to ensure compliance. Recommendation is a 12-month phased implementation, including training and a 3,000-client pilot test.
Complexity, Cost, Regulatory Alignment	Estimated TCO of $305,000.00, $150,000.00 of which is directly related to development and implementation. While the model is compliant with 393.0662, FS, 65G-4.0214, FAC, and HB 1103, testing is required to determine compliance with other regulations. There is a risk of discriminatory impact, which may cause challenges. *See the appendix for additional details on preliminary cost estimates.*
Changes	Model 4 was designed to automatically adjust dynamically to changes in the data and can be adjusted easily based on policy changes. This process may require a resource with additional statistical expertise.

8 Model 5 – Ridge Regression

Description: Model 5 – Ridge Regression (L2 Regularization) adds a penalty to independent variables that have especially large coefficients. This process helps prevent the model from overfitting and reduces variance. This approach is applied when there are concerns about data being highly correlated (Multicollinearity), resulting in a model that is more stable.

Results: Model 5 has ~106% (Test R^2 = 0.5204) higher predictive accuracy than the existing algorithm (Model 5b).

Additional Factors: Model 5 produces the most stable predictions, with reduced overfitting and improved generalization. However, it also involves abstract and complex concepts and may create regulatory concerns.

8.1.1 Algorithm

To calculate the actual iBudget services amount a client will receive, the results of the ridge regression are squared to support interpretability (i.e., yielding a monetary outcome). The budget allocation calculation for this model is displayed in Equation 5: Model 5 iBudget Allocation Calculation.

Equation 5: Model 5 iBudget Allocation Calculation

$$Budget_i = \left(\hat{\beta}_0 + \sum_{j=1}^{54} \hat{\beta}_j^{Ridge}(\lambda^*) \cdot SD_j \cdot X_{ij} \right)^2$$

For additional information and analysis related to Model 5, see Appendix Section 12.5, Model 5 Additional Details.

8.1.2 Model 5 Implementation Feasibility and Impact

The results of Model 5's implementation feasibility study are provided in Table 7: Model 5 Implementation Feasibility Results.

Table 7: Model 5 Implementation Feasibility Results

Categories	Model 5
Impact	
Accuracy, Reliability, and Robustness	Model results in ~106% (Test $R^2 = 0.5204$) higher predictive accuracy than the baseline.
Sensitivity to Outliers and Missing Data	Coefficient shrinkage eliminates the need for outlier exclusion and protects the model from performance degradation when dealing with missing data.
Feasibility	
Implementation	The model has similar technical requirements to the original model but requires significant training and documentation around the L2 penalization process. ISF recommends a 12-month phased rollout, including a pilot.
Complexity, Cost, Regulatory Alignment	Cost analysis estimates a total TCO of $220,000.00, $115,000.00 of which are directly related to development and implementation. The model is compliant with existing regulations. *See the appendix for additional details on preliminary cost estimates.*
Changes	Dynamic updates are supported, though the algorithm's stability minimizes the need for frequent updates. This process may require a resource with additional statistical expertise.

9 Model 6 – Log-Normal Regression

Description: Model 6 – Log-Normal Regression assumes that budget allocations follow a log-normal distribution. This type of distribution is particularly useful when modeling positive, skewed data (like budget allocations).

Results: Model 6 has ~92% (Test $R^2 = 0.4596$) higher predictive accuracy than the existing algorithm (Model 5b).

Additional Factors: This algorithm handles the skewness of the data well, has an intuitive, multiplicative interpretation, and offers a superior distributional fit for the data. However, it adds retransformation complexity and may lead to regulatory hurdles.

9.1.1 Algorithm

To calculate the actual iBudget services amount a client will receive, the results of the log-normal regression are exponentiated to support interpretability (i.e., yielding a monetary outcome). The budget allocation calculation for this model is displayed in Equation 6: Model 6 iBudget Allocation Calculation.

Equation 6: Model 6 iBudget Allocation Calculation

$$\text{Budget}_i = \exp\left(\hat{\mu}_i\right) \cdot \frac{1}{n}\sum_{j=1}^{n}\exp(\hat{\epsilon}_j)$$

For additional information and analysis related to Model 6, see Appendix Section 12.6, Model 6 Additional Details.

9.1.2 Model 6 Implementation Feasibility and Impact

The results of Model 6's implementation feasibility study are provided in Table 8: Model 6 Implementation Feasibility Results.

Table 8: Model 6 Implementation Feasibility Results

Categories	Model 6
Impact	
Accuracy, Reliability, and Robustness	Model results in ~92% (Test R^2 = 0.4596) higher predictive accuracy than baseline
Sensitivity to Outliers and Missing Data	Log-normal regression naturally compresses outliers, making exclusion unnecessary. This allows the algorithm to leverage 100% of the training data.
Feasibility	
Implementation	Similarities to the existing algorithm make the technical implementation a straightforward process. However, resources must be dedicated to training and documentation. A12–18-month rollout with a 2,500-client pilot test is recommended.
Complexity, Cost, Regulatory Alignment	Cost analysis estimates a total TCO of $185,000, $100,000 of which is directly related to implementation and development. Model 6 is transparent and interpretable but will require changes to existing rules to remain compliant with 65G-4.0214, FAC. *See the appendix for additional details on preliminary cost estimates.*
Changes	Coefficients are very stable due to the log transformation, but the model still allows for fast emergency updates and has the capability to scale coefficients with appropriate changes. This process may require a resource with additional statistical expertise.

10 Model 9 – Random Forest

Description: Model 9 – Random Forest leverages decision trees, flowchart-like structures, which split data based on feature values to make predictions. The model averages the results of those decision trees to arrive at its predictions.

Results: Model 9 has ~164% (Test R^2 = 0.6575) higher predictive accuracy than the existing algorithm (Model 5b), representing the largest improvement.

Additional Factors: Model 9 requires minimal data preprocessing, automatically captures feature interactions, does not assume a distribution over the data, is resistant to outliers and noise, and is fully compliant. It also has limited interpretability.

10.1.1 Algorithm

To calculate the actual iBudget services amount a client will receive, the average predictions of 500 decision trees is calculated, according to the formula displayed in Equation 7: Model 9 Budget Allocation Calculation.

Equation 7: Model 9 Budget Allocation Calculation

$$Budget_i = \frac{1}{B}\sum_{b=1}^{B} T_b(x)$$

For additional information and analysis related to Model 9, see Appendix Section 12.7, Model 9 Additional Details.12.7

10.1.2 Model 9 Implementation Feasibility and Impact

The results of Model 9's implementation feasibility study are provided in Table 9: Model 9 Algorithm Implementation Feasibility Results.

Table 9: Model 9 Algorithm Implementation Feasibility Results

Categories	Model 9
Impact	
Accuracy, Reliability, and Robustness	Model results in ~164% (Test R^2 = 0.6575) higher predictive accuracy than baseline.
Sensitivity to Outliers and Missing Data	Ensemble methodology naturally makes the model robust to outliers and missing data.
Feasibility	
Implementation	Implementation requires additional technical infrastructure and computational power. Ongoing maintenance is necessary to prevent performance drift.
Complexity, Cost, Regulatory Alignment	Three-year TCO is estimated at $500,000.00, $145,000.00, which is directly related to implementation and development. Model is well aligned with existing state and federal regulations. *See the appendix for additional details on preliminary cost estimates.*
Changes	This model can be recalibrated as desired, using sufficient statistical experience. This model would require strategic communication to the public to describe changes to the model based on the complex mathematical approach.

11 Next Steps

Following the submission of this deliverable, ISF will review the contents with APD and make any needed changes based on APD’s consolidated feedback. ISF will then complete D4, Recommended Algorithm, which will be accompanied by evidence demonstrating improved accuracy, reliability, and person-centered outcomes. An impact analysis, D5, will be conducted for the recommended algorithm and submitted at the same time.

12 Appendix – Detailed Model Descriptions

The following information is based on ISF's assessment; confirmation from APD is required.

The following sections provide additional details on the alternative algorithms, Model 1 – Model 9, described in the body of this deliverable. These details provide information related to key requirements for the iBudget algorithm according to statute, HB 1103, and the iBudget Algorithm Study scope of work. These details include:

- Algorithm for Individual Adjustments: Provides mathematical details and model formulations
- Sensitivity to Outliers and Missing Data: Describes how the model handles extreme data points and missing data points, including the accuracy and reliability of outcomes
- Assessment of Robustness: Documents the assessment of the model's ability to produce similar results under different conditions
- Implementation Feasibility: Provides information on the practicality of APD's ability to execute the model. *Note that implementation assessments are based on ISF's experience and knowledge and are only meant to represent estimates.*
- Complexity, Cost, and Regulatory Alignment: Documents the assessment of these implementing factors
- Feasibility of Changes: Describes the efforts required to adopt the model

Variable Mapping Matrix

Table 10: Variable Mapping Matrix provides the variable mapping matrix used for all the alternative algorithm models, except for Model 9.

Table 10: Variable Mapping Matrix

Variable	Type	Meaning
X_1	Independent	LivingSetting
X_2	Independent	LOSRI
X_3	Independent	OLEVEL
X_4	Independent	BLEVEL
X_5	Independent	FLEVEL
X_6	Independent	PLEVEL
X_7	Independent	Age
X_8	Independent	AgeGroup
X_9	Independent	County
X_{10}	Independent	BSum
X_{11}	Independent	FSum
X_{12}	Independent	PSum
X_{13}	Independent	FHFSum
X_{14}	Independent	SLFSum

Variable	Type	Meaning
X_{15}	Independent	SLBSum
X_{16}	Independent	SupportedLiving_x_LOSRI
X_{17}	Independent	Age_X_Bum
X_{18} - X_{54}	Independent	QSI Q14-50
Y	Dependent	The predicted annual iBudget waiver allocation monetary amount

12.1 Model 1 Additional Details

12.1.1 Algorithm for Individual Adjustments

Model 1 – Updated Model 5B, is formulated identically to the existing algorithm used by APD (Model 5b), but uses updated coefficients designed with the use of current data.

This model is a multiple linear regression, Multiple-linear Regression which is a derivative of the classic slope-intercept formula (y=mx+b), used for modelling a straight line. The difference with regression is the attempt to identify the line that best fits the data (e.g., drawing a fitted line through a scatterplot wherein the datapoints are evenly distributed along the line, and their distance from the line is minimized). This distance from the line is measured by a minimized Sum of Squared Errors (SSE) term (i.e., taking the distance from each point to the line, summing the values, and then squaring). The line with the best fit indicates an ability to insert new numbers into the equation (i.e., numbers specific to each client), and achieve a relatively expected result (i.e., a result along the slope of the line). This can help facilitate planning efforts and demonstrate suitability of the funding allocations.

In the case of APD, the algorithm is intended to account for several factors that ultimately yield an appropriate monetary amount that should sufficiently support the client, yielding use of a multiple regression model.

The Model 1 formula is displayed in Equation 8: Model 1 Formulation.

Equation 8: Model 1 Formulation

$$\sqrt{y_i} = \beta_0 + \sum_{j=1}^{p} \beta_j x_{ij} + \epsilon_i$$

The components of this formula include:

- Y_i = The dependent variable (DV). Annual expenditure for iBudget service waiver client i
- i = Indicates each iBudget services waiver client
- j = Indicates each predictor for iBudget services
- X_{ij} = Value of predictor j for each iBudget service waiver client
- p = 54 features

- β_0 = Intercept coefficient
    - Also known as the constant, and indicates the value of the DV when all the independent variables (IV) are equal to 0
- β_j = Updated regression coefficients
    - These values reflect the average change in the DV for every one-unit increase in the IV
    - It is important to note that a negative value indicates that with each unit change, the coefficient is decreasing. When interpreting this equation (or others), recognizing when this is appropriate based on the reality of the coefficients being assessed is critical. In this case, a positive value is increasing the amount of the DV.
- ε_i = Random error term for iBudget service waiver clients i.
    - This term represents the difference (i.e., error) between the observed and predicted values in the regression.

The key decision logic, assumptions and thresholds used in Model 1 are described as:

- **Minimum Allocation:** $5,000.00, in compliance with the regulatory floor
- **Outlier Exclusion:** Top 9.40% of residuals removed before coefficient estimation
    - This was implemented due to its application in the original model design. Current advanced data analytic techniques include several options for handling outliers, and it is generally desirable to exclude the least amount possible so that the model can have better real-life performance.
- **Edge Case Handling:** Predictions below the minimum allocation and cases above the maximum allocation require manual review.
- **Normal Distribution:** Assumed for the error term and iBudget allocations
    - A normal distribution for iBudget allocations helps facilitate a proportional allocation of funds across the client population and allows for more valid hypothesis testing.
    - The error term requires a normal distribution due to the Gauss Markov-Theory **Error! Reference source not found.**, which assumes residuals/errors follow an assumed normal distribution. This aligns with the intent of modeling a "best fit" line to the regression equation.
    - With larger sample sizes, the Central Limit Theory will usually account for any exhibited non-normality, but in smaller sample sizes, the effect of a non-normal distribution can be magnified and have impacts on the results.

To calculate the actual iBudget services amount a client will receive, the results of the multiple linear regression equation are squared to support interpretability (i.e., yielding a monetary outcome). The budget allocation calculation for this is displayed in Equation 9: Model 1 iBudget Allocation Calculation.

Equation 9: Model 1 iBudget Allocation Calculation

$$Budget_i = \left(\hat{\beta}_0 + \sum_{j=1}^{54} \hat{\beta}_j X_{ij}\right)^2$$

This is the formula for Model 1 version 1.0 with coefficients calculated using FY 22-23, FY 23-24, and FY 24-25 data and trained on a total of 102,727 iBudget system waiver records.

The following reflects the training and testing data splits used to train Model 5:

- **Training Data (80%):** 74,647 Client-year records after outlier removal
- **Testing Data (20%):** 20,541 Client-year records

12.1.2 Accuracy, Reliability, and Robustness

Table 11: Model 1 Accuracy Metrics displays the primary regression metrics that were used to measure the prediction accuracy of Model 1.

Table 11: Model 1 Accuracy Metrics

Metric	Value	Interpretation
R^2 Improvement (%)	+95.09 (Test R^2 = 0.4932)	Percent improvement in R^2 between Model 1 and the current algorithm (Model 5b).
Root Mean Squared Error (RMSE) ($)	32,378.78	RMSE measures the square root of the average squared distance between predictions and their actual value (also known as error). As a result, RMSE penalizes larger errors more heavily. A lower RMSE means a more accurate model.
Mean Absolute Error (MAE) ($)	21,444.48	MAE measures the average absolute distance between predicted and actual values (error). MAE treats all errors equally and is more robust to outliers than RMSE.
Mean Absolute Percentage Error (MAPE) (%)	315.21	MAPE expresses MAE accuracy as a percentage, by comparing absolute error to the actual value.

12.1.3 Sensitivity to Outliers and Missing Data

Outliers are managed and excluded from Model 1 according to the originally developed process using the following thresholds:

- **Outlier Threshold:** Studentized Residuals (residual error standardized over the standard deviation of the dataset) of 1.645 or higher are removed. This corresponds to approximately 10% removal.
- **Detection Method:** Cook's Distance and Leverage Analysis
- **Treatment:** Exclusion from training data (8.84% of sample)
- **Documentation:** Exclusions are logged with justification

12.1.4 Implementation Feasibility

The technical requirements to run Model 1 are detailed below:

- **System Compatibility:** Direct integration with APD databases is required
- **Software:** Standard OLS implementation in R, Python, SAS
- **Computation:** ~0.1 second per allocation
- **Memory Requirements:** Minimal
- **Database:** Compatible with existing systems

Model 1 is immediately deployable as it represents a direct update of the existing operational model. No system architecture changes are required. The model should be deployed in a parallel run with the existing model to verify consistency, through a phased rollout.

12.1.5 Complexity, Cost, and Regulatory Alignment

Model 1 has algorithmic complexity of $O(n)$, meaning its complexity is linear in terms of the amount of data used to train it. It is fully interpretable and transparent, with all coefficients visible. Annual re-estimation of the model is required to maintain peak predictive performance.

Table 12: Model 1 Cost Breakdown displays provides preliminary estimates of total cost:

Table 12: Model 1 Cost Breakdown

	Unit Cost	Hours	Total Cost
Development Cost	$250	100	$25,000.00
Implementation Cost	$250	40	$10,000.00
Training Costs	$250	0	$0.00
Annual Operational Costs	$250	60	$15,000.00
3-year Cost of Ownership	$250		$80,000.00

If system integration, automated retraining, or MLOps capabilities are required, the total three-year cost may double (e.g., ~$160,000), reflecting the added effort for deployment, monitoring, and compliance.

The cost estimates provided represent ISF's professional judgment based on available information at the time of analysis and are not intended to be definitive or interpreted as a statement of fact.

Model 1 is fully compliant with 393.0062, FS, HB 1103, and the federal Medicaid requirements. To be complaint with 65G-4.0214, FAC, the coefficients must be updated to coincide with the algorithm.

12.1.6 Feasibility of Changes

Model 1 is fully interpretable, with Git-based version control to facilitate a full and transparent audit trail. In the case of changes to appropriations, Model 1's coefficients can be scaled proportionally. In the case of a policy update, there is a 30-day implementation window, with the capability for a 48-hour deployment for emergencies.

Model 1 facilitates constant monitoring and automated reporting around when retraining is required:

- **Performance Monitoring:** Weekly automated reporting
- **Drift Detection:** Kolmogorov-Smirnov testing monthly
- **Retraining Triggers:** 5.00% performance degradation, otherwise annual
- **Validation:** Holdout set refreshed quarterly

12.2 Model 2 Additional Details

12.2.1 Algorithm for Individual Adjustments

Model 2 – Generalized Linear Model replaces the square root transformation used in Model 1 with a more appropriate approach for addressing the expenditure data since it is positive and right-skewed. The formula uses a logarithmic transformation to again improve interpretability and stabilize variance since the data is non-linear. This is expressed below in Equation 10: Model 2 Formulation

Equation 10: Model 2 Formulation

$$\log(\mathbb{E}[Y_i|X_i]) = \beta_0 + \sum_{j=1}^{p} \beta_j X_{ij}$$

The components of this formula include:

- $\mathbb{E}(Y_i|X_i)$ = The DV. The expected annual expenditure for iBudget service waiver client i, given all predictor variables X_i
- i = Indicates each iBudget services waiver client
- j = Indicates each predictor for iBudget services
- p = 54
- β_0 = Intercept coefficient
- β_j = Updated regression coefficients
- X_{ij} = Value of predictor j for iBudget service waiver client i

Where:

- Y_i follows a Gamma distribution with shape parameter α and scale parameter θ
- The variance of $\mathbb{E}(Y_i|X_i)$ can be described by the quadratic variance function described below:
  - $Var(Y_i|X_i) = \phi \cdot \mathbb{E}(Y_i|X_i)^2$, where ϕ is the dispersion parameter

To calculate Y_i, the results of the regression must be exponentiated to return the results to the original scale. The budget allocation calculation in Model 2 is displayed in Equation 11: Model 2 iBudget Allocation Calculation.

Equation 11: Model 2 iBudget Allocation Calculation

$$Budget_i = \exp\left(\hat{\beta}_0 + \sum_{j=1}^{54} \hat{\beta}_j X_{ij}\right)$$

The key decision logic and thresholds used in Model 2 are described as:

- **Natural Boundary:** Predictions that are automatically positive due to the use of exponential transformations
- **Minimum Allocation:** $5,000.00, in compliance with the regulatory floor
- **Maximum Allocation:** $350,000.00 (waiver cap)
- **Outlier Exclusion:** Robust standard errors using a sandwich estimator
- **Edge Case Handling:** Predictions below the minimum set to $5,000.00; cases above the maximum allocation require manual review

This is the formula for Model 2 version 1.0 with coefficients calculated using FY 22-23, FY 23-24, and FY 24-25 data and trained on a total of 102,727 iBudget system waiver records.

The following reflects the training and testing data splits used to train Model 5:

- **Training Data (80%):** 82,186 Client-year records after outlier removal
- **Testing Data (20%):** 20,541 Client-year records

12.2.2 Accuracy, Reliability, and Robustness

Table 13: Model 2 Accuracy Metrics displays the primary regression metrics that were used to measure the prediction accuracy of Model 2.

Table 13: Model 2 Accuracy Metrics

Metric	Value	Interpretation
Improvement (%)	+68.55 (Test R^2 = 0.4261)	Percent improvement in R^2 between Model 2 and the current algorithm (Model 5b).
Root Mean Squared Error (RMSE) ($)	34,455.13	RMSE measures the square root of the average squared distance between predictions and their actual value (also known as error). As a result, RMSE penalizes larger errors more heavily. A lower RMSE means a more accurate model.
Mean Absolute Error (MAE) ($)	23,887.37	MAE measures the average absolute distance between predicted and actual values (error). MAE treats all errors equally and is more robust to outliers than RMSE.

Metric	Value	Interpretation
Mean Absolute Percentage Error (MAPE) (%)	411.41	MAPE expresses MAE accuracy as a percentage, by comparing absolute error to the actual value.

12.2.3 Sensitivity to Outliers and Missing Data

Due to its formulation and underlying assumptions, Model 2 is naturally robust to outliers, as Gamma distributions naturally accommodate right skewed data (outliers). Outliers were managed according to the following approaches:

- **Detection Method:** Deviance residuals greater than or equal to 3
- **Treatment:** None necessary as the model naturally down-weighted outliers
- **Impact:** Model allowed for inclusion of all observations, which improved model coverage
- **Documentation:** Influence diagnostics were computed for all cases

12.2.4 Implementation Feasibility

The technical requirements to run Model 2 are detailed below:

- **System Compatibility:** Direct integration with APD databases is required
- **Software:** R/SAS/Python with generalized linear model (GLM) capabilities
- **Computation:** < 5 seconds
- **Memory Requirements:** Minimal
- **API Deployment:** REST endpoint with 50ms response time

To deploy Model 2, ISF recommends the following activities as part of implementation:

- **Staff Training:** 2 week staff education on GLM interpretation
- **Regulatory Update:** Modify FAC 65G-4.0214 for log-link
- **Pilot Testing:** 1,000 customer subset validation
- **Phased Rollout:** Regional deployment

Transitioning from Model 5b to Model 2 requires:

- **Stakeholder education:** Multiplicative vs. additive effects
- **Appeals Process Update:** New explanation templates for percentage changes
- **Budget Impact Analysis:** Customer-level allocation changes
- **Documentation:** Comprehensive guides for all user levels

12.2.5 Complexity, Cost, and Regulatory Alignment

Model 2 has algorithmic complexity of $O(np)$, meaning its complexity is linear in terms of the amount of data used to train it times the number of predictors p used in each row of data. It is fully interpretable and transparent, with all coefficients visible. To maintain and update the model, statistical expertise is required.

Table 14: Model 2 Cost Breakdown displays estimates of total cost:

Table 14: Model 2 Cost Breakdown

	Unit Cost	Hours	Total Cost
Development Cost	$250	340	$85,000.00
Implementation Cost	$250	180	$45,000.00
Training Costs	$250	0	$0.00
Annual Operational Costs	$250	120	$30,000.00
3-year Cost of Ownership	$250		$220,000.00

The cost estimates provided represent ISF's professional judgment based on available information at the time of analysis and are not intended to be definitive or interpreted as a statement of fact.

An analysis of Model 2's potential alignment with regulatory rules indicates:

- **FS 393.0662:** Compliant with documentation
- **FAC 65G-4.0214:** Requires rule update for log-link function
- **CMS Requirements:** Meets statistical validity standards
- **Appeals Process:** Clear explanation possible via linear predictor

12.2.6 Feasibility of Changes

Model 2 is fully interpretable with statistical expertise. Git-based version control allows the production of a full and transparent audit trail. In the case of changes to appropriations, Model 2's linear predictor can be scaled uniformly. In the case of policy changes, coefficients can be easily updated, and constraints can be easily implemented. Under emergency situations, the model can be updated and re-deployed in 72 hours.

Model 2 facilitates constant monitoring and automated reporting around when retraining is required:

- **Performance Monitoring:** Monthly automated reporting
- **Drift Detection:** Pearson residual monitoring
- **Retraining Schedule:** Annual or upon 3.00% performance degradation

12.3 Model 3 Additional Details

12.3.1 Algorithm for Individual Adjustments

Model 3 – Robust Linear Regression maintains the current algorithm's formulation but accounts for the concern with a high level of outliers (i.e., 9.40% were excluded in the original model development). The core mode, which still uses a square root transformation for interpretability, is displayed in Equation 12: Model 3 Formulation.

Equation 12: Model 3 Formulation

$$\sqrt{Y_i} = \beta_0 + \sum_{j=1}^{p} \beta_j X_{ij} + \varepsilon_i$$

With robust linear regression, the main difference is that a Huber Loss function is used to replace the MSE and MAE for the handling of residuals. Huber's objective loss function is found in Equation 13: Huber's Objective Loss Function for Reweighting.

Equation 13: Huber's Objective Loss Function for Reweighting

$$\rho(r) = \begin{cases} \frac{1}{2}r^2 & \text{if } |r| \leq k \\ k|r| - \frac{1}{2}k^2 & \text{if } |r| > k \end{cases}$$

The components of the robust linear regression formula include:

- Y_i = The DV. The expected annual expenditure for iBudget service waiver client i
- X_{ij} = Value of predictor j for iBudget service waiver client i
- β_0 = Intercept coefficient
- p = 54 (number of parameters)
- i = Indicates each iBudget services waiver client
- j = Indicates each predictor for iBudget services
- β_j = Updated regression coefficients
- $r = \frac{Y_i - \hat{Y}_i}{s}$ = standardized residual (error)
- s = Robust scale estimate
- k = 1.345 (tuning constant for 95% efficiency)
- $p(r)$ = Penalty assigned to each residual
- Weight function: $w(r) = \min\left(1, {}^{k}/_{|r|}\right)$

The budget allocation calculation in Model 3 is displayed in Equation 14: Model 3 iBudget Allocation Calculation.

Equation 14: Model 3 iBudget Allocation Calculation

$$Budget_i = \left(\hat{\beta}_0^R + \sum_{j=1}^{54} \hat{\beta}_j^R X_{ij}\right)^2$$

The iterative estimation process employed by Model 3 is described below:

- Initialize weights with coefficients of existing algorithm
- Calculate residuals and the robust scale estimate
- Compute Huber weight for each observation

- Update coefficients via weight function
- Iterate until coefficient updates are nonsignificant (close to zero)
- Final allocation is calculated using converged coefficients

The key decision logic and thresholds used in Model 3 are described as:

- **Minimum Allocation:** $5,000.00, in compliance with the regulatory floor
- **Maximum Allocation:** $350,000.00 (waiver cap)
- **Tuning Constant:** 1.35 (95% Gaussian efficiency)
- **Weight Threshold:** Observations with weight < 0.5 flagged for review
- **Convergence:** Maximum 50 iterations

This is the formula for Model 3 version 1.0 with coefficients calculated using FY 22-23, FY 23-24, and FY 24-25 data and trained on a total of 102,727 iBudget system waiver records.

The following reflects the training and testing data splits used to train Model 5:

- **Training Data (80%):** 82,186 Client-year records after outlier removal
- **Testing Data (20%):** 20,541 Client-year records

12.3.2 Accuracy, Reliability, and Robustness

Table 15: Model 3 Accuracy Metrics displays the primary regression metrics that were used to measure the prediction accuracy of Model 3.

Table 15: Model 3 Accuracy Metrics

Metric	Value	Interpretation
Improvement (%)	+96.95 (Test R^2 = 0.4979)	Percent improvement in R^2 between Model 3 and the current algorithm (Model 5b).
RMSE ($)	32,228.95	RMSE measures the square root of the average squared distance between predictions and their actual value (also known as error). As a result, RMSE penalizes larger errors more heavily. A lower RMSE means a more accurate model.
MAE ($)	21,413.06	MAE measures the average absolute distance between predicted and actual values (error). MAE treats all errors equally and is more robust to outliers than RMSE.
MAPE (%)	356.23	MAPE expresses MAE accuracy as a percentage, by comparing absolute error to the actual value.

12.3.3 Sensitivity to Outliers and Missing Data

The iterative re-weighting process employed by Model 3 eliminates the need for outlier exclusion. For more detail into the weighting process, see below:

- **Transparent Weighting:** Each client receives a weight between 0 and 1
- **Breakdown Point:** 50.00% theoretical maximum robustness
- **Efficiency:** 95.00% relative to base case
- **Documentation:** Weight rationale provided for each allocation

12.3.4 Implementation Feasibility

The technical requirements to run Model 3 are detailed below:

- **System Compatibility:** Direct integration with APD databases is required; database should be enhanced to include client weights
- **Software:** R (robustbase), SAS (ROBUSTREG), Python (statsmodels)
- **Computation:** 3-5 seconds for full convergence
- **Memory Requirements:** 512MB for weight matrix storage
- **Parallelization:** Possible for large-scale deployment

An assessment of APD's operational readiness to implement Model 3 indicated:

- **Staff Training:** Four-hour workshop on robust methods, two-hour session on weight interpretation
- **Documentation:** Weight explanation generator
- **Pilot Phase:** 2,000 client pilot recommended
- **Rollout Timeline:** Six-month phased implementation

12.3.5 Complexity, Cost, and Regulatory Alignment

Analysis into the technical complexity of Model 3 yields:

- **Algorithmic Complexity:** Iterative approach has moderate complexity
- **Interpretability:** Coefficients identical to original interpretation
- **Weight Explanation:** Simple, threshold-based narrative
- **Maintenance:** Annual re-estimation with weight monitoring

Table 16: Model 3 Cost Breakdown displays estimates of total cost:

Table 16: Model 3 Cost Breakdown

	Unit Cost	Hours	Total Cost
Development Cost	$250	260	$65,000.00
Implementation Cost	$250	140	$35,000.00
Training Costs	$250	80	$20,000.00
Annual Operational Costs	$250	100	$25,000.00
3-year Cost of Ownership	$250		$195,000.00

The cost estimates provided represent ISF's professional judgment based on available information at the time of analysis and are not intended to be definitive or interpreted as a statement of fact.

An analysis of Model 3's potential alignment with regulatory rules indicates:

- **FS 393.0662:** Compliant
- **FAC 65G-4.0214:** Requires minor rule update for weight documentation
- **HB 1103:** Weights provide additional transparency
- **Appeals Process:** Clear explanation possible via linear predictor
- **Due Process:** All clients included, with none excluded

12.3.6 Feasibility of Changes

Model 3 is fully interpretable with statistical expertise. Git-based version control allows the production of a full and transparent audit trail. The model can dynamically adapt to changes in data, with real-time weight recalculation. Weight history is also maintained to assist versioning control.

Model 3 facilitates constant monitoring and reporting whenever retraining is required:

- **Weight Distribution:** Weekly monitoring
- **Performance Metrics:** Monthly robust R^2 tracking
- **Outlier Patterns:** Quarterly analysis
- **Retraining Trigger:** Annual or upon 3.00% performance degradation

12.4 Model 4 Additional Details

12.4.1 Algorithm for Individual Adjustments

Model 4 maintains the current algorithm's formulation, as seen in Equation 15: Model 4 Formulation.

Equation 15: Model 4 Formulation

$$\sqrt{y_i} = \beta_0 + \sum_{j=1}^{p} \beta_j x_{ij} + \epsilon_i$$

While extending the current algorithm through the incorporation of precision weights based on variance heteroscedasticity, with weights as seen in Equation 16: Model 4 Weights,

Equation 16: Model 4 Weights

$$w_i = \text{clip}\left(\frac{1}{\hat{\sigma}_i^2/\text{mean}(\hat{\sigma}^2)}, w_{\min}, w_{\max}\right)$$

where $\hat{\sigma}_i^2$ is the estimated variance for observation i based on the logit found in Equation 17: Model 4 Variance Estimation.

Equation 17: Model 4 Variance Estimation

$$\log(\hat{\sigma}_i^2) = \gamma_0 + \gamma_1 \log(\hat{Y}_i) + \gamma_2 \text{LivingSetting}_i + \gamma_3 \text{SupportLevel}_i$$

With the WLS estimator minimizing as seen in Equation 18: Model 4 WLS Estimator.

Equation 18: Model 4 WLS Estimator

$$\sum_{i=1}^{n} w_i \left(\sqrt{Y_i} - \beta_0 - \sum_{j=1}^{54} \beta_j X_{ij}\right)^2$$

The components of this formula include:

- Y_i = The DV. The expected annual expenditure for iBudget service waiver client i, given all predictor variables X_i
- X_{ij} = Value of predictor j for iBudget service waiver client i
- β_0 = Intercept coefficient
- $p = 54$
- i = Indicates each iBudget services waiver client
- j = Indicates each predictor for iBudget services
- β_j = Updated regression coefficients
- $\hat{\sigma}_i^2$ = Estimated variance for observation i
- w_i = Weight for observation i
- γ_i = Variance model coefficient

The budget allocation calculation in Model 4 is displayed in Equation 19: Model 4 iBudget Allocation Calculation.

Equation 19: Model 4 iBudget Allocation Calculation

$$Budget_i = \left(\hat{\beta}_0^{WLS} + \sum_{j=1}^{54} \hat{\beta}_j^{WLS} X_{ij}\right)^2$$

The estimation process employed by Model 4 is described below as a two-stage process:

- **Stage 1: Variance Function Estimation**
  - Run the current algorithm to measure residuals e_i
  - Calculate the squared residuals e_i^2
  - Estimate the variance function via regression of $\log(e_i^2)$
  - Predict variances $\hat{\sigma}_i^2$ for all observations
- **Stage 2: Weighted Estimation**
  - Calculate weights $w_i = 1/\hat{\sigma}_i^2$
  - Normalize weights: $\widetilde{w} = w_i \cdot n / \sum w_i$
  - Apply equity caps: $w_i \in [0.2,5]$ to prevent extreme weighting
  - Estimate WLS coefficients with capped weights

The key decision logic and thresholds used in Model 4 are described as:

- **Minimum Allocation:** \$5,000.00, in compliance with the regulatory floor
- **Maximum Allocation:** \$350,000.00 (waiver cap)
- **Weight Bounds:** $w_i \in [0.2,5]$ to prevent domination
- **Demographic Checks:** Weight distribution verified across protected classes
- **Variance Modeling:** Limited to non-discriminatory predictors

This is the formula for Model 4 version 1.0 with coefficients calculated using FY 22-23, FY 23-24, and FY 24-25 data and trained on a total of 102,727 iBudget system waiver records.

The following reflects the training and testing data splits used to train Model 5:

- **Training Data (80%):** 82,186 Client-year records after outlier removal
- **Testing Data (20%):** 20,541 Client-year records

12.4.2 Accuracy, Reliability, and Robustness

Table 17: Model 4 Accuracy Metrics displays the primary regression metrics that were used to measure the prediction accuracy of Model 4.

Table 17: Model 4 Accuracy Metrics

Metric	Value	Interpretation
Improvement (%)	+104.55 (Test R^2 = 0.5171)	Percent improvement in R^2 between Model 4 and the current algorithm (Model 5b).
RMSE ($)	31,605.60	RMSE measures the square root of the average squared distance between predictions and their actual value (also known as error). As a result, RMSE penalizes larger errors more heavily. A lower RMSE means a more accurate model.
MAE ($)	21,947.27	MAE measures the average absolute distance between predicted and actual values (error). MAE treats all errors equally and is more robust to outliers than RMSE.
MAPE (%)	445.91	MAPE expresses MAE accuracy as a percentage by comparing absolute error to the actual value.

12.4.3 Sensitivity to Outliers and Missing Data

The WLS process employed by Model 4 eliminates the need for outlier exclusion. Details related to the outlier handling process include:

- **Outlier Detection:** Standardized weighted residuals > 3
- **Treatment:** Weight reduction, not exclusion
- **Impact:** High-variance cases receive lower weights
- **Coverage:** 100% of clients included
- **Documentation:** Weight rationale provided for each allocation

12.4.4 Implementation Feasibility

The technical requirements to run Model 4 are detailed below:

- **System Compatibility:** Direct integration with APD databases is required; the database should be enhanced to include client variance
- **Software:** Standard statistical packages (R, SAS, SPSS)
- **Computation:** Two-stage process < 2 seconds in total
- **Memory Requirements:** 256MB for weight matrix storage
- **API:** REST endpoint with weight transparency

ISF recommends the following activities and processes as part of the implementation and deployment of Model 4:

- **Staff Training:** Six-hour workshop on WLS methodology, two-hour equity safeguards training, two-hour variance interpretation session
- **Documentation:** Comprehensive weight explanation system
- **Pilot Phase:** 3,000 client pilot with equity monitoring recommended
- **Rollout Timeline:** 12-month phased implementation with safeguards

12.4.5 Complexity, Cost, and Regulatory Alignment

Analysis of the technical complexity of Model 4 yields:

- **Algorithmic Complexity:** Two-stage estimation has moderate complexity
- **Interpretability:** Coefficients maintain original interpretation
- **Weight Explanation:** Variance-based narrative required
- **Maintenance:** Quarterly variance function updates

Table 18: Model 4 Cost Breakdown displays estimates of total cost:

Table 18: Model 4 Cost Breakdown

	Unit Cost	Hours	Total Cost
Development Cost	$250	380	$95,000.00
Implementation Cost	$250	220	$55,000.00
Training Costs	$250	140	$35,000.00
Annual Operational Costs	$250	160	$40,000.00
3-year Cost of Ownership	$250		$305,000.00

The cost estimates provided represent ISF's professional judgment based on available information at the time of analysis and are not intended to be definitive or interpreted as a statement of fact.

An analysis of Model 4's potential alignment with regulatory rules indicates:

- **FS 393.0662:** Compliant pending equity documentation
- **FAC 65G-4.0214:** Requires rule update for weight methodology
- **HB 1103:** Explainable with weight documentation
- **Civil Rights:** Extensive testing required
- **ADA Compliance:** Must prove there is no discriminatory impact

Model 4's variance-based weighting raises equity concerns and potential legal vulnerabilities:

- **Complex Disabilities:** Customers with sever behavioral challenges often have high-variance costs, receiving systematically lower weights
- **Rare Conditions:** Atypical support needs may be down-weighted due to limited similar cases
- **Transitional Periods:** Major life changes (aging, health deterioration) increase variance
- **Protected Classes:** If variance correlates with race, ethnicity, or disability type, disparate impact may occur
- **ADA Section 504:** Potential violation if weighting disadvantages people with more severe disabilities
- **Equal Protection:** Constitutional concerns if algorithm produces differential treatment
- **Civil Rights Act:** Risk of disparate impact claims
- **State Regulations:** May conflict with Florida's individualized assessment mandate

12.4.6 Feasibility of Changes

Model 4 is designed to allow for dynamic adaptation. The variance calculations should be re-estimated quarterly, while the weights should be recalibrated annually. Policy changes can be implemented within a 60-day window, with weight override capabilities in the case of an emergency.

Model 4 facilitates constant monitoring and reporting around when retraining is required:

- **Weight Distribution:** Weekly monitoring by demographics
- **Variance Patterns:** Monthly analysis
- **Equity Metrics:** Continuous, automated monitoring
- **Performance Metrics:** Weighted and unweighted R^2 monitoring

12.5 Model 5 Additional Details

12.5.1 Algorithm for Individual Adjustments

Model 5 – Ridge Regression maintains the current algorithm's formulation, with the addition of an L2 penalty to handle multicollinearity. Model 5's formulation is described in Equation 20: Model 5 Formulation.

Equation 20: Model 5 Formulation

$$\min_{\beta} \sum_{i=1}^{n} \left(\sqrt{Y_i} - \beta_0 - \sum_{j=1}^{54} \beta_j X_{ij} \right)^2 + \lambda \sum_{j=1}^{54} \beta_j^2$$

The components of this formula include:

- Y_i = The DV. The expected annual expenditure for iBudget service waiver client i
- X_{ij} = Value of predictor j for iBudget service waiver client i
- β_0 = Intercept coefficient
- i = Indicates each iBudget services waiver client
- j = Indicates each predictor for iBudget services
- β_j = Updated regression coefficients
- λ = Regularization parameter (tuning constant)
- $\hat{\beta}^{Ridge} = (X^T X + \lambda I)^{-1} X^T Y$

The budget allocation calculation in Model 5 is displayed in Equation 21: Model 5 Budget Allocation Calculation.

Equation 21: Model 5 Budget Allocation Calculation

$$Budget_i = \left(\hat{\beta}_0 + \sum_{j=1}^{54} \hat{\beta}_j^{Ridge}(\lambda^*) \cdot SD_j \cdot X_{ij}\right)^2$$

ISF leveraged a cross-validation (CV) approach for selecting a value for λ, the regularization parameter:

- 10-fold CV for λ selection
- Grid search: $\lambda \epsilon [0.001,1000]$ on log scale
- Optimal $\lambda^* = 46.415888$ minimizes CV error

The key decision logic and thresholds used in Model 5 are described as:

- **Minimum Allocation:** $5,000.00, in compliance with the regulatory floor
- **Maximum Allocation:** $350,000.00 (waiver cap)
- **Shrinkage Factor:** 6.3% average reduction
- **Correlation Handling:** Automatic via ridge penalty
- **Stability:** All coefficients bounded

This is the formula for Model 5 version 1.0 with coefficients calculated using FY 22-23, FY 23-24, and FY 24-25 data and trained on a total of 102,727 iBudget system waiver records.

The following reflects the training and testing data splits used to train Model 5:

- **Training Data (80%):** 82,186 Client-year records after outlier removal
- **Testing Data (20%):** 20,541 Client-year records

12.5.2 Accuracy, Reliability, and Robustness

Table 19: Model 5 Accuracy Metrics displays the primary regression metrics that were used to measure the prediction accuracy of Model 5.

Table 19: Model 5 Accuracy Metrics

Metric	Value	Interpretation
Improvement (%)	+105.85 (Test R^2 = 0.5204)	Percent improvement in R^2 between Model 5 and the current algorithm (Model 5b).
RMSE ($)	31,498.20	RMSE measures the square root of the average squared distance between predictions and their actual value (also known as error). As a result, RMSE penalizes larger errors more heavily. A lower RMSE means a more accurate model.
MAE ($)	21,967.84	MAE measures the average absolute distance between predicted and actual values (error). MAE treats all errors equally and is more robust to outliers than RMSE.
MAPE (%)	446.61	MAPE expresses MAE accuracy as a percentage, by comparing absolute error to the actual value.

12.5.3 Sensitivity to Outliers and Missing Data

Ridge regressions naturally reduce outlier influence through coefficient shrinkage. As a result, Model 5 leverages 100% of the sample data available with no outlier exclusion. Even when including outliers, the algorithm has superior stability when compared to the current algorithm.

12.5.4 Implementation Feasibility

The technical requirements to run Model 5 are detailed below:

- **System Compatibility:** Same requirements as the existing algorithm
- **Software:** All major packages support ridge regression
- **Computation:** <1 second with pre-computed λ
- **Memory Requirements:** 256MB for weight matrix storage

ISF recommends the following activities and processes as part of the implementation and deployment of Model 5:

- **Staff Training:** Eight hours of training on regularization concepts
- **Documentation:** λ selection process
- **Pilot Phase:** 2,000 client pilot recommended
- **Rollout Timeline:** 12-month phased implementation with training and education

12.5.5 Complexity, Cost, and Regulatory Alignment

Analysis of the technical complexity of Model 5 yields:

- **Algorithmic Complexity:** Moderate complexity – penalty concept
- **Interpretability:** Can be challenging; requires understanding on the shrinkage explanation
- **Maintenance:** Annual λ (parameter) re-tuning.

Table 20: Model 5 Cost Breakdown displays estimates of total cost:Table 20: Model 5 Cost Breakdown displays estimates of total cost:

Table 20: Model 5 Cost Breakdown

	Unit Cost	Hours	Total Cost
Development Cost	$250	300	$75,000.00
Implementation Cost	$250	160	$40,000.00
Training Costs	$250	120	$30,000.00
Annual Operational Costs	$250	100	$25,000.00
3-year Cost of Ownership	$250		$220,000.00

The cost estimates provided represent ISF's professional judgment based on available information at the time of analysis and are not intended to be definitive or interpreted as a statement of fact.

An analysis of Model 5's potential alignment with regulatory rules indicates:

- **FS 393.0662:** Compliant – requires penalty explanation
- **FAC 65G-4.0214:** Compliant – must retain all 22 predictors
- **HB 1103:** Coefficient shrinkage complicates explanation, but still explainable
- **Appeals Process:** Complex coefficient interpretation

12.5.6 Feasibility of Changes

Model 5 supports dynamic updates through λ tuning, which should be (at a minimum) optimized annually and tracked for version control. Coefficient updates can be made as often as quarterly. One built in-advantage of Model 5 is its stability, which makes the model less sensitive to data shifts, making it less necessary to update the model as frequently as other models.

The following metrics should be tracked and monitored over time:

- **Effective Degrees of Freedom:** Track reduction from 22
- **Shrinkage Factor:** Monitor the average across time
- **Prediction Stability:** Monitor weekly variance
- **Retuning Trigger:** 5% performance drop

12.6 Model 6 Additional Details

12.6.1 Algorithm for Individual Adjustments

Model 6 – Log-Normal Regression replaces the square root transformation of the original model with the natural logarithm, as displayed in Equation 22: Model 6 Formulation.

Equation 22: Model 6 Formulation

$$\log(Y_i) = \beta_0 + \sum_{j=1}^{54} \beta_j X_{ij} + \varepsilon_i$$

The components of this formula include:

- Y_i = The DV. The expected annual expenditure for iBudget service waiver client i
- X_{ij} = Value of predictor j for the iBudget service waiver client i
- β_0 = Intercept coefficient
- i = Indicates each iBudget services waiver client
- j = Indicates each predictor for iBudget services
- β_j = Updated regression coefficient for the predictor j

Where:

- $Y_i \sim \text{LogNormal}(\mu_i, \sigma^2)$ - DV is distributed according to a log-normal distribution, with a mean of μ_i and a standard deviation of σ^2
- $\mu_i = \beta_0 + \sum_{j=1}^{22} \beta_j X_{ij} + \epsilon_i$
- ϵ_i = Error term for client i
- $\mathbb{E}[Y_i|X_i] = \exp\left(\mu_i + \frac{\sigma^2}{2}\right)$ – Bias correction
- $\text{Median}[Y_i|X_i] = \exp(\mu_i)$

The budget allocation calculation utilized by Model 6 is displayed in Equation 23: Model 6 Budget Allocation Calculation.

Equation 23: Model 6 Budget Allocation Calculation

$$\text{Budget}_i = \exp(\hat{\mu}_i) \cdot \frac{1}{n} \sum_{j=1}^{n} \exp(\hat{\epsilon}_j)$$

This is the formula for Model 6 version 1.0 with coefficients calculated using FY 22-23, FY 23-24, and FY 24-25 data and trained on a total of 102,727 iBudget system waiver records.

The following reflects the training and testing data splits used to train Model 5:

- **Training Data (80%):** 82,186 Client-year records after outlier removal
- **Testing Data (20%):** 20,541 Client-year records

12.6.2 Accuracy, Reliability, and Robustness

Table 21: Model 6 Accuracy Metrics displays the primary regression metrics that were used to measure the prediction accuracy of Model 6.

Table 21: Model 6 Accuracy Metrics

Metric	Value	Interpretation
Improvement (%)	+81.80% (Test R^2 = 0.4596)	Percent improvement in R^2 between Model 6 and the current algorithm (Model 5b).
RMSE ($)	33,434.11	RMSE measures the square root of the average squared distance between predictions and their actual value (also known as error). As a result, RMSE penalizes larger errors more heavily. A lower RMSE means a more accurate model.
MAE ($)	23,180.43	MAE measures the average absolute distance between predicted and actual values (error). MAE treats all errors equally and is more robust to outliers than RMSE.
MAPE (%)	400.37	MAPE expresses MAE accuracy as a percentage by comparing absolute error to the actual value.

12.6.3 Sensitivity to Outliers and Missing Data

The log-normal regression naturally dampens and compresses outliers, making exclusion unnecessary and allowing the model to leverage 100.00% of the dataset available for training. An assessment on the influence of outliers yields:

- **High-Cost Cases:** Log transformation prevents undue leverage – predictions remain stable
- **Cook's Distance:** All observations have modest influence on fitted model
- **DFBETAS:** No single case substantially alters any coefficient estimate
- **Robustness:** Model performance is stable when high-cost cases removed in sensitivity analysis

12.6.4 Implementation Feasibility

The technical requirements to run Model 6 are detailed below:

- **System Compatibility:** Same requirements as the existing algorithm
- **Software:** All major packages support log transformations
- **Computation:** <0.5 seconds
- **API:** Simple exponential retransformation

ISF recommends the following activities and processes as part of the implementation and deployment of Model 6:

- **Staff Training:** Six hours of training on log interpretation
- **Documentation:** Percentage change explanations
- **Pilot Phase:** 2,500 client pilot
- **Rollout Timeline:** 12-18-month phased implementation with validation

12.6.5 Complexity, Cost, and Regulatory Alignment

Analysis into the technical complexity of Model 6 yields:

- **Algorithmic Complexity:** Same as current model. The log transformation is a relatively simple mathematical transformation.
- **Interpretability:** Multiplicative effects intuitive to interpret
- **Maintenance:** Standard regression updates

Table 22: Model 6 Cost Breakdown displays estimates of total cost:Table 22: Model 6 Cost Breakdown displays estimates of total cost:

Table 22: Model 6 Cost Breakdown

	Unit Cost	Hours	Total Cost
Development Cost	$250	260	$65,000.00
Implementation Cost	$250	140	$35,000.00
Training Costs	$250	100	$25,000.00
Annual Operational Costs	$250	80	$20,000.00
3-year Cost of Ownership	$250		$185,000.00

The cost estimates provided represent ISF's professional judgment based on available information at the time of analysis and are not intended to be definitive or interpreted as a statement of fact.

An analysis of Model 6's potential alignment with regulatory rules indicates:

- **FS 393.0662:** Requires a justification of log transformation
- **FAC 65G-4.0214:** Compliant pending a rule update for log transformation
- **HB 1103:** Compliant, as percentage changes are explainable
- **Appeals Process:** Compliant as multiplicative effects clear requirements

12.6.6 Feasibility of Changes

Model 6 has very high coefficient stability due to the log transformation. As such, relatively fewer updates should be required over time as performance should remain stable. In the case of appropriation adjustments, coefficients scale. Model 6 supports 48-hour update capabilities in case of an emergency.

The following metrics should be tracked and monitored over time:

- **Residual Normality:** Check monthly
- **Retransformation Bias:** Check quarterly
- **Performance:** R^2 (log and original scale)
- **Retraining:** Annual or 5.00% degradation

12.7 Model 9 Additional Details

12.7.1 Algorithm for Individual Adjustments

Model 9 – Random Forest regression is an ensemble learning method that combines predictions from multiple decision trees. A decision tree is a flowchart-like structure that splits data based on feature values to make predictions. This is a non-parametric approach that captures complex interactions and non-linearities without requiring explicit specification or assuming a distribution on the data. Model 9 uses a collection of 500 random forests and generates predictions according to Equation 24: Model 9 Random Forest FormulaEquation 24: Model 9 Random Forest Formula.

Equation 24: Model 9 Random Forest Formula

$$\hat{y} = \frac{1}{B}\sum_{b=1}^{B} T_b(x)$$

Where:

- $\hat{y}$ = The predicted iBudget allocation
- x =Original input data
- B = Total number of random trees (500)
- T_b =The prediction from tree b

The key hyperparameters of the model include:

- Maximum tree depth: 15
- Minimum samples split: 8
- Minimum samples in leaf: 3

The following process was used to train Model 9:

- For each tree in the forest:
    1. Sample n datapoints with replacement
    2. At each node, consider a set of random features
    3. Splits to minimize squared error
    4. Grows until reaching stopping criteria

This is the formula for Model 9 version 1.0 with coefficients calculated using FY 22-23, FY 23-24, and FY 24-25 data and trained on a total of 102,727 iBudget system waiver records.

The following reflects the training and testing data splits used to train Model 9:

- **Training Data (80%):** 82,186 Client-year records after outlier removal
- **Testing Data (20%):** 20,541 Client-year records

Variable Mapping Matrix

Table 23: Model 9 Variable Mapping Matrix provides the variable mapping matrix used for Model 9.

Table 23: Model 9 Variable Mapping Matrix

Variable	Type	Meaning
X_1	Independent	LivingSetting
X_2	Independent	LOSRI
X_3	Independent	OLEVEL
X_4	Independent	BLEVEL
X_5	Independent	FLEVEL

Variable	Type	Meaning
X_6	Independent	PLEVEL
X_7	Independent	Age
X_8	Independent	AgeGroup
X_9	Independent	BSum
X_{10}	Independent	FSum
X_{11}	Independent	PSum
X_{12}	Independent	FHFSum
X_{13}	Independent	SLFSum
X_{14}	Independent	SLBSum
X_{15}	Independent	SupportedLiving_x_LOSRI
X_{16}	Independent	Age_X_Bum
X_{17} - X_{53}	Independent	QSI Q14-50
Y	Dependent	The predicted annual iBudget waiver allocation monetary amount

12.7.2 Accuracy, Reliability, and Robustness

Table 24: Model 9 Accuracy MetricsTable 24: Model 9 Accuracy Metrics displays the primary accuracy metrics that were used to measure the prediction accuracy of Model 9.

Table 24: Model 9 Accuracy Metrics

Metric	Value	Interpretation
Improvement (%)	+160.09 (Test R^2 = 0.6575)	Percent improvement in R^2 between Model 9 and the current algorithm (Model 5b).
RMSE ($)	26,617.51	RMSE measures the square root of the average squared distance between predictions and their actual value (also known as error). As a result, RMSE penalizes larger errors more heavily. A lower RMSE means a more accurate model.
MAE ($)	18,709.44	MAE measures the average absolute distance between predicted and actual values (error). MAE treats all errors equally and is more robust to outliers than RMSE.
MAPE (%)	400.27	MAPE expresses MAE accuracy as a percentage, by comparing absolute error to the actual value.

12.7.3 Sensitivity to Outliers and Missing Data

Model 9 is naturally robust to outliers and missing data due to its ensemble formulation:

- Individual trees may be affected by extreme values in their bootstrap sample
- Other trees, trained on different samples, are unaffected
- Averaging across 150 trees dampens the influence of any single outlier
- Median-based splits (rank ordering) are inherently robust to extreme values

Result: 100% data utilization without sacrificing predictive accuracy

12.7.4 Implementation Feasibility

ISF identified the following as possible risks to implementation:

- High computational complexity of the model requires sophisticated infrastructure (cloud recommended)
- Low interpretability of results requires trained staff and the development of feature importance tools
- Model is tightly fit to the data; performance drift over time will degrade performance in the absence of structured, periodic retraining procedures

ISF recommends the following implementation strategy should Model 9 be implemented:

- **Infrastructure Setup** (1 month)**:** Python environment and model hosting
- **Pilot Testing** (2 months)**:** 5,000 customer subset validation
- **Parallel Run** (6 months)**:** Side-by-side with Model 5b
- **Training Program** (3 weeks)**:** Staff education on ensemble methods
- **Phased Rollout** (2 months)**:** Regional deployment with monitoring
- **Full Implementation** (1 month)**:** Statewide deployment

The following maintenance procedures should be implemented along with Model 9:

- **Quarterly Retraining:** Update with new data to minimize chance of drift
- **Annual Review:** Comprehensive model evaluation
- **Feature Monitoring:** Track importance changes
- **Performance Tracking:** Monitor drift and degradation

12.7.5 Complexity, Cost, and Regulatory Alignment

Table 25: Model 9 Cost Breakdown displays estimates of total cost:

Table 25: Model 9 Cost Breakdown

	Unit Cost	Hours	Total Cost
Development Cost	$250	340	$85,000.00
Implementation Cost	$250	380	$95,000.00
Training Costs	$250	260	$65,000.00
Annual Operational Costs	$250	340	$85,000.00
3-year Cost of Ownership	$250		$500,000.00

The cost estimates provided represent ISF's professional judgment based on available information at the time of analysis and are not intended to be definitive or interpreted as a statement of fact.

Model 9 is compliant and aligned with the requirements of FAC 65G-4.0213, FAC 65G-4.0214, and FAC 65G-4.0215. It also satisfies the Federal CMS waiver requirements.

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Recommendations and Impact Analysis

Florida Agency for Persons with Disabilities

2025 iBudget Algorithm Study

October 28, 2025

Deliverable 4 – Algorithm Recommendations

Deliverable 5 – Algorithm Impact Analysis

Table of Contents

Table of Tables

Acronyms

Acronym	Definition
APD	Agency for Persons with Disabilities
D	Deliverable
FY	Fiscal Year
MI	Mutual Information
PDP	Partial Dependence Plots
SHAP	SHapley Additive exPlanations Values
FS	Florida Statute
CMS	Centers for Medicare and Medicaid Services
HCBS	Home and Community-Based Services
FAC	Florida Administrative Code
QSI	Questionnaire for Situational Information
SAN	Significant Additional Needs
HB	House Bill
FH	Family Home
NC	Not Classified (Group Home without RH service)
RMSE	Root Mean Squared Error
CRA	Community Residential Alternative
LD	Learning Disability
ADHD	Attention-Deficit/Hyperactivity Disorder
PERS	Personal Emergency Response System
PDF	Portable Document Format
HCS	Home and Community-based Services
CA	California
IDRD	Intellectual Disabilities and Related Disabilities

Revision History

Version	Date	Author	Notes
V1	10/17/2025	ISF	D4 and D5 for APD Review
V2	10/28/2025	ISF	D4 and D5 for APD Review

1 Executive Summary

The Home and Community-Based Services (HCBS) iBudget system is a component of Florida's Medicaid waiver program that enables individuals with developmental disabilities to receive personalized care and support within their homes and communities. Central to this system is an algorithm that determines each person's individualized budget based on key factors such as age, living setting, and information from the Questionnaire for Situational Information (QSI), supplemented by additional assessments when needed. Administered by the Agency for Persons with Disabilities (APD), the program currently supports more than 36,000 individuals, with an additional 19,000 individuals on the pre-enrollment list.

The original iBudget waiver algorithm model, Model 5b, was developed by professors Tao and Niu in 2015 under the auspices of Florida State University (FSU). When recent data from fiscal year (FY) 2023–24 is applied to the model, the model's performance shows a high variance between iBudget waiver prediction and actual claims data compared to its original 2015 estimates. As a result, alternative models were developed and tested to identify the most effective approach for meeting the goals of the iBudget system.

Each model was evaluated based on its statistical performance, alignment with HCBS program objectives, and ability to reflect real-world service needs. After multiple iterations and comparative analyses, the model that demonstrated the strongest performance, consistency across participant groups, and overall balance was selected as the recommended approach.

Model 9, Random Forest, was ultimately selected as the recommended approach, as it demonstrated stronger overall performance compared to the other models tested, as well as compared to the current Model 5b. Figure 1: Model 5b and Model 9 Comparison provides an overview of the initial outcomes of the assessment of Model 5b using current FY 2023-2024 data, as well as the recommended algorithm, Model 9.

Figure 1: Model 5b and Model 9 Comparison

	Difference Between Model 1 (Model 5b Re-evaluation) and Model 9
Variance Between Claims and Budget Amount	Improved 33%
Error Magnitude	Substantial Reduction
Outliers	None

This algorithm plays a critical role beyond budget calculations as it directly influences how resources are allocated, which in turn affects the services, levels of care, and person-centered supports available to individuals. Accordingly, this analysis recommends a phased implementation approach, paired with rigorous validation and ongoing monitoring, to ensure that algorithmic enhancements lead to tangible improvements in service delivery and participant outcomes. Recognizing that changes to algorithms within disability services can have far-reaching impacts on individual well-being, this approach underscores the need for careful consideration of potential unintended consequences and implementation challenges.

Finally, during the review, ISF determined that the iBudget waiver currently provides a robust set of services to meet diverse participant needs. However, should APD determine that adding new or modified services is appropriate, it should conduct in-depth research to understand how each would integrate within the existing service array, estimate potential utilization and true service costs, and determine whether additional funding may be required through a Legislative Budget Request. Implementation would also require federal approval and updates to the iBudget program's rules, handbook, training, and public education materials.

2 Background

The mission of APD is to support individuals with disabilities and their families in living, learning, and working within their communities by creating multiple pathways to possibilities.[1] APD serves individuals with disabilities, as defined in section 393.063(11), Florida Statutes (FS), through identifying service needs, connecting them with appropriate social, medical, behavioral, residential, and therapeutic supports, and funding the required level of services through applicable programs.

The United States Centers for Medicare & Medicaid Services' (CMS) HCBS Medicaid waiver allows the federal government to waive rules that typically apply to Medicaid programs. The use of the HCBS waiver provides states with the opportunity to achieve specific goals and offers services that would not typically be covered by Medicaid.[2] The Florida Agency for Health Care Administration, the state's primary Medicaid administering agency, partners with APD to provide the HCBS waiver program to APD's service population.

The HCBS Medicaid waiver is administered by APD through the iBudget system, enabling APD clients to receive medically necessary support and services that facilitate living in the community. The iBudget system offers a variety of social, medical, behavioral, therapeutic, and residential services to individuals with developmental disabilities. As of 2025, there are more than 36,000 individuals enrolled in the program, with a pre-enrollment list of more than 19,000 people. Each client's iBudget amount is calculated using the allocation algorithm in Rule 65G-4.0214, Florida Administrative Code (FAC), based on age, living setting, and QSI factors,[3] plus any significant additional needs (SAN) identified in individual reviews.

During the 2025 legislative session, the Florida Legislature passed House Bill (HB) 1103, which was subsequently signed into law on June 10, 2025. This legislation requires APD to contract for a study to review, evaluate, and identify recommendations regarding the algorithm required under section 393.0662, FS, the iBudget implementing statute.

In response to HB 1103, APD engaged ISF to conduct the iBudget Algorithm Study. The study involves activities to support the development of recommendations to ensure the up-to-date and accurate allocation of resources to Florida's most vulnerable citizens, aligning with both statutory requirements and principles of person-centered care. These activities include:

- Assessment of the current algorithm, including expenditure data (Deliverable (D) 2)
- Identification of potential alternative algorithms (D3)
- Recommendation of one algorithm for APD's implementation (D4)
- Impact analysis of the recommended algorithm (D5)
- Production of the iBudget Algorithm Study report as required in HB 1103 (D6 and D7)

[1] Agency for Persons with Disabilities, State of Florida. (2025, August). APD – Agency for Persons with Disabilities. Retrieved September 12, 2025, from https://apd.myflorida.com/index.htm

[2] Centers for Medicare & Medicaid Services. (n.d.). Home & Community-Based Services 1915(c). Medicaid. U.S. Department of Health and Human Services. Retrieved September 12, 2025, from https://www.medicaid.gov/medicaid/home-community-based-services/home-community-based-services-authorities/home-community-based-services-1915c

[3] Agency for Persons with Disabilities. (2015, May 21). Florida questionnaire situational information (version 4.0).

3 Approach

The approach to the development of these deliverables encompassed rigorous statistical research and validation, as well as other external research, described below. Appendix Section 8.1, Scientific Report, provides the scientific report for the iBudget Algorithm Study, which includes additional information on the methodology described in this section, as well as additional statistical and coding information.

Algorithm Recommendation

Following the development and refinement of the alternative algorithms provided in D3 of the study, Alternative Algorithms, ISF assessed the performance of the algorithms compared to the goals of the iBudget system and APD's HCBS program. Following multiple iterations of running the algorithm with actual APD data, the recommendation for the model(s) was selected based on performance. The analysis encompassed six FYs of data (September 1, 2019– August 31, 2025, specifically to account for normal billing cycles), applying information-theoretic measures, statistical association diagnostics, and multicollinearity controls to identify optimal predictors for cost modeling. To determine the most appropriate algorithmic model to recommend, performance was compared to the baseline performance of Model 1, which has the same computational structure as the currently used Model 5b with updated data. By establishing Model 1 (with outlier removal) as the baseline, a benchmark was created and anchored to the current operational standard that stakeholders understand, allowing subsequent models to be evaluated not merely on their standalone merit but on their incremental value over existing practice. This approach is consistent with established statistical methodology, where baseline models serve as controls in comparative studies, enabling researchers to isolate the specific contribution of methodological innovations (robust estimation, regularization, ensemble methods) while holding the feature set and data preparation pipeline relatively constant.

Additional Waiver Services

To determine the potential additional services for APD to consider, ISF conducted a review of HCBS waiver service offerings in 10 states. The 10 states were selected based on feedback provided during the stakeholder interviews, population size, and the uniqueness of services provided. The 10 states include Ohio, Pennsylvania, New York, Texas, California, Michigan, South Carolina, Tennessee, Illinois, and Georgia.

Impact Analysis

To produce the impact analysis, an economic analysis was produced for each alternative algorithm. A conservative budget approach was used to ensure adequate funding to cover cases where the model under-predicts actual costs, which helps to account for model uncertainty. A comparative analysis was then conducted of each model compared to Model 0 (which is Model 5b with current costing information) as the baseline. The analysis used actual APD data to estimate actual and predicted costs, as well as the total conservative budget.

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Algorithm Recommendation

Florida Agency for Persons with Disabilities

2025 iBudget Algorithm Study

October 17, 2025

Deliverable 4 - Algorithm Recommendation

4 Algorithm Recommendation

Model 9 employs Random Forest regression, an ensemble learning method that is a machine learning model that uses multiple decision trees to collectively make better predictions. In this instance, the Random Forest regression combined predictions from 150 decision trees trained on bootstrap samples of the data (a method that helps the data become amenable to random sampling methods, such as what is required for a Random Forest regression). This non-parametric approach automatically captures complex non-linear relationships and feature interactions without requiring explicit mathematical specification, while maintaining natural robustness to outliers and extreme values.

Each tree in a Random Forest is trained on a random subset of data, and at each decision point, a random subset of features is considered. This randomness helps to reduce overfitting and increases the model's ability to generalize to new data. For classification problems, each tree "votes" for a class, and the majority vote determines the final prediction. For regression problems, such as this exploration, the predicted value is the average of all trees' outputs.

Random Forests are widely used because they are robust, can handle large datasets with many features, and provide insights into feature importance, highlighting which variables have the greatest impact on predictions.

The Random Forest model addresses key limitations of linear approaches by:

- **Automatic Interaction Detection:** Discovers feature interactions without manual specification through recursive partitioning
- **Non-Linear Modeling:** Captures complex relationships that linear models cannot represent
- **Natural Robustness:** Ensemble averaging provides inherent protection against outliers
- **100% Data Utilization:** No client exclusions required, improving fairness
- **Built-In Validation:** Out-of-bag error estimation provides ongoing performance monitoring

Interpretability Through Importance: Feature importance rankings facilitate policy understandingTable 1: Model 9 Comparative Performance, Model 9 consistently outperforms the updated Model 5b (Model 1)[4] across key metrics, including predictive accuracy, cost efficiency, and data utilization. The comparison highlights improvements in R^2, demonstrating the enhanced performance and reliability of Model 9.

Table 1: Model 9 Comparative Performance

Performance Factors	Model 1 (Model 5b Re-evaluation)	Model 9
Test R^2	0.4931	0.6575
Root Mean Squared Error (RMSE) ($)	32,359.08	26,617.51
Outliers Removed (%)	0.00	0.00

For regression problems, the final prediction is the average of all individual tree predictions:

[4] Model 1 maintains the exact Model 5b structure while updating and re-specifying coefficients with current data and retaining outliers.

Equation 1: Random Forest Regression Equation

$$\hat{y}_{\mathrm{RF}}(x) = \frac{1}{B}\sum_{b=1}^{B}\hat{y}_b(x)$$

Where B is the number of trees (150 in this implementation) and $\hat{y}_b(x)$ is the prediction from the b^{th} tree.

Key Findings:

- **Living Setting:** Performance varies across living settings, with differences attributable to distinct cost structures and support intensity levels.
- **Age Groups:** Model performance is consistent across age groups, indicating age-related features capture cost differences effectively.
- **Cost Quartiles:** Performance typically varies by cost level, with the model performing best in the middle quartiles where the bulk of observations lie.

4.1 Advantages and Limitations

Table 2: Advantages and Disadvantages of Model 9 presents the key advantages and disadvantages of the recommended model.

Table 2: Advantages and Disadvantages of Model 9

Advantages	Disadvantages
Less sensitive to outliers observed in training data	High model complexity
Improved cost efficiency	Results require training to reliably interpret
Produces stable and transparent predictions	Relatively higher technical requirements
Well aligned with regulatory compliance requirements	Periodic re-training recommended

Model 9 demonstrates several key strengths. Its robustness comes from naturally handling outliers without the need for exclusions. Transparency is supported through feature importance rankings, which enhance interpretability for stakeholders. Stability is ensured by ensemble averaging, reducing prediction volatility. Finally, the model meets regulatory compliance requirements of section 393.0662, FS, when paired with appropriate explainability tools, ensuring both accountability and defensibility.

By avoiding the removal of outliers, Model 9 ensures that all clients receive evidence-based budget predictions without systematically excluding high-cost or unusual cases. This approach allows the model to naturally accommodate legitimate extreme support needs, enhancing the fairness, transparency, and defensibility of budget allocations.

While Model 9 offers substantial benefits, several implementation challenges should be acknowledged. Stakeholders may perceive model complexity as a “black box.” Staff will require comprehensive training to understand ensemble methods, along with explainability tools. Moreover, Random Forests have a key limitation in that they cannot reliably extrapolate beyond the range of training data. Predictions are inherently constrained by the minimum and maximum values observed in the training set for each region, meaning that new or unusual consumer profiles—such as previously unseen combinations of characteristics—may not be predicted accurately. To address this limitation and maintain model relevance, it is important to regularly retrain the algorithm with updated data, ensuring it reflects current trends and behaviors.

While Random Forests provide fast predictions, they require more resources for training and storage compared with simpler linear models. For example, training a Random Forest may take approximately 1.94 seconds, compared with less than 1 second for an ordinary least squares model, and the model must store 150 decision trees rather than a single set of coefficients. Additionally, implementation requires a compatible computing environment, such as Python with scikit-learn. Despite these higher requirements, they remain modest and easily manageable with modern computing infrastructure. These results are summarized in Table 3: Summary Specification.

Table 3: Summary Specification

Component	Specification
Algorithm	Random Forest Regression
Transformation	None
Outlier Method	None (100% inclusion)
Features	53 (auto-selected, minus county)[5]
Training Time	1.94 seconds
Prediction Time	< 1 ms per consumer
Memory Requirements	150 trees storage

[5] County indicator was found to degrade out-of-sample performance due to the non-parametric nature of a Random Forest

To further enhance transparency and trust, several explainability tools should be applied:

- **SHapley Additive exPlanations (SHAP) Values:** Quantify each feature's contribution to an individual prediction, providing insight at the observation level.[6]
  Partial Dependence Plots (PDPs): Visualize the average effect of each feature across the dataset, highlighting general trends.
  Individual Tree Paths: Trace the decision path for a specific observation, offering a detailed view of the model's logic.

Implementing these tools is essential not only for regulatory compliance but also for effectively communicating results to stakeholders, mitigating the "black box" perception, and ensuring the model can be confidently applied in practice.

[6] SHAP values provide mathematically rigorous feature attribution, transforming Model 9's ensemble predictions into transparent, dollar-scale explanations as required by F.S. 393.0662. SHAP values provide a mathematically consistent framework that decomposes each prediction into additive feature contributions. This allows directional interpretation (positive or negative impact), person-specific explanations, and explicit accounting for feature interactions, producing results that are more transparent and policy relevant for the iBudget analytical framework.

5 Additional Waiver Services

APD offers a robust service array for clients to choose from to construct individual service plans that best meet their needs, including escalating levels of care across eight service categories, listed in Section 5.1, Services For Consideration. In addition to the algorithm assessment requirements listed in HB 1103, this legislation also mandated that the study "consider whether any waiver services that are not currently funded through the algorithm can be funded through the current algorithm or an alternative algorithm." The analysis of additional waiver services provides details on HCBS waiver services provided in other states, both states with similar population sizes and states that provide services mentioned in stakeholder interviews. The full scope of state services researched is documented in Appendix Section 8.2, Other States' Services

5.1 Services For Consideration

Following the research of other states' services, ISF compared the identified services to Florida's service array as described in the iBudget Handbook. The results of the analysis indicated that many of the services are provided in some fashion in Florida. Four types of services were identified, listed in Table 4appeared to be unique offerings or would take Florida's current, similar service offering a step further. These services were selected based on the fit of each service in Florida's iBudget current service array, which includes the following service categories:

- Life Skills Development
- Supplies and Equipment
- Personal Supports
- Residential Services
- Support Coordination
- Wellness and Therapeutic Supports
- Transportation
- Dental Services

Table 4: Additional Service Considerations provided below, outlines the identified services APD may consider adding to the current iBudget waiver program in the future, and a comparison of the identified additional services to Florida's current service array and estimated costs, which vary by state and level of individual need. Should APD determine that the inclusion of these, or other, services are appropriate to incorporate into Florida's HCBS waiver, the following activities should be considered:

- How the service integrates into the current service array, including the category and scope of service types (such as living setting, in-home supports, etc.)
- Estimation of the potential number of iBudget clients who may utilize the services
- Identification of the actual costs of services in the Florida system of care and the corresponding potential need to request additional program funding via a Legislative Budget Request
- Addition of the new service in the Medicaid waiver, which requires federal approval
- Addition of the new service to existing iBudget program infrastructure, including administrative code, the HCBS handbook, staff and waiver support coordinator training, and public education

In addition to these activities, the adoption of additional services would include the requirement for changes to the Florida Administrative Code, which may create administrative, financial, and legal barriers. Additionally, there are complex regulatory frameworks between federal and state laws which create complexities for service additions potentially causing conflict or creating ambiguity, which would slow down the ability to implement additional services.

Table 4: Additional Service Considerations

Service	General Service Description	Service Gap Comparison	Relevant Florida Service Category	Potential Algorithmic Related Variables	Estimated Cost of Service Peer States
Host Home	A host home is a private residence in a residential area in which the occupant, owner, or lessee provides Community Residential Alternative (CRA) services to persons with developmental disabilities who are not related to the occupant owner or lessee by blood or marriage. Georgia services costs are provided based on a capped cost of services provided. Texas service costs are based on the level of care requirements and broken out into a cost per day for the level of care required in the host home.	This service (residential option) is currently not offered in Florida.	Residential Services	Living Setting: Independent Living & Supported Living	**Georgia:** $155.56/day $4,200/month $50,402/year **Texas:** Intermittent $72.56/day Limited $76.14/day Extensive $94.07/day Pervasive $119.18/day Pervasive+ $147.84/day
Service Effectiveness: A comparative analysis of Host Home Care vs. Traditional Care Facilities in Texas identified that Host Homes offer more personalized, family-like environments which help to foster a deeper connection and understanding of the individuals' needs and preferences. Additionally, host homes offer a space where individuals have more emotional comfort and warmth when compared to a traditional care facility allowing individuals to feel more "at home." Host homes also offer strong community integration, allowing individuals to experience social interaction and engagement within the community more easily than if they were in a traditional care facility. While host homes offer many valuable opportunities for individuals with lower levels of care needs, it is not always the best option for individuals with very complex medical needs or those who require specialized medical equipment and around-the-clock clinical monitoring. Overall, host homes have shown their effectiveness for increasing the quality of life for individuals, supporting stronger community integration, and demonstrating cost-efficiency as they tend to have lower operational costs than a traditional care facility. [7]					

[7] Jenkins, M. (2023, November 26). *Host Home Care vs. Traditional Care Facilities: A Comparative Analysis*. Above & Beyond Caring. https://abchcs.com/host-home-care-vs-traditional-care-facilities-a-comparative-analysis/

Service	General Service Description	Service Gap Comparison	Relevant Florida Service Category	Potential Algorithmic Related Variables	Estimated Cost of Service Peer States
Training and Counseling for Unpaid Caregivers	Training for unpaid caregivers is a service provided through the state to support caregivers who are typically family members and is usually provided at no cost to the family. Training for the caregivers is tailored based on the level of support the individual client needs. Illinois service costs are based on an hourly rate for the counseling provided to the unpaid caregiver. California's service cost is based on the benefits a caregiver receives by participating in the Cal Grows program.	This service is currently not offered in Florida through the iBudget program.	Personal Supports	N/A	**Illinois:** Counseling Only $33.13/hour **California:** Participant Benefit $1,088/total **Michigan:** Cost not available

Service	General Service Description	Service Gap Comparison	Relevant Florida Service Category	Potential Algorithmic Related Variables	Estimated Cost of Service Peer States
Service Effectiveness: Specific studies for caregiver training and counseling in the HCBS space are limited in scope and number. However, there is evidence suggesting the importance and effectiveness of this service being provided to caregivers to improve the overall quality of life for both the client and their caregiver. Oversight and training are critical components of a successful caregiver program. California utilizes service delivery either through an Agency Model, in which contracted entities provide services, or through a Self-Directed Model. Service delivery, regardless of the model, is structured around the person-centered assessment of need based on Section 2401 of the Affordable Care Act. Each county submits a plan identifying annual goals with quality improvement and assurance oversight:[8,9] ● Routine case file reviews ● Home visits ● Data review and analysis ● Targeted case reviews ● Verification of receipt of services According to a study by Westat for the Administration for Community Living, responses showed that mental health is correlated between caregivers and recipients; recipients with better mental health had caregivers with better mental health and fewer emotional problems. Greater care recipient satisfaction with social activities was also related to higher caregiver quality of life rating.[10] Well-designed randomized clinical trials have shown that effective caregiver interventions tend to share several characteristics, including assessments of caregiver risks and needs, tailored interventions that address multiple areas of risk or caregiver need and preferences, and active involvement of caregivers in skills training. The research also suggests the potential that some caregiver interventions reduce the resource use of care recipients by delaying nursing home placement, reducing re-hospitalizations, and shortening hospital stays.[11] Preliminary studies related to training and counseling for caregivers have shown positive results that may lead to improved mental health, increased client satisfaction, and reduced reliance on institutional settings.					

[8] Community First Choice (CFC) 1915 (k) Program. The Centers for Medicare and Medicaid. https://www.medicaid.gov/medicaid/home-community-based-services/home-community-based-services-authorities/community-first-choice-cfc-1915-k

[9] ACA SECTION 2401, Community First Choice Option (Section 1915(k) of the Social Security Act); California State Plan Amendment: Research Summary. National Opinion Research Center. December 4, 2012. https://www.medicaid.gov/medicaid/home-community-based-services/downloads/ca-cfc-spa-matrix_0.pdf

[10] Avison, C., Brock, D., Campione, J., Hassell, S., Rabinovich, B., Ritter, R., Severynse, J., & Yang, D. (December 5, 2018). Outcome evaluation of the National Family Caregiver Support Program (Final Report). Westat. Administration for Community Living. https://acl.gov/sites/default/files/programs/2018-12/Caregiver_Outcome_Evaluation_Final_Report.pdf

[11] National Academies of Sciences, Engineering, and Medicine. (2016). 5 Programs and supports for family caregivers of older adults. *Families caring for an aging America* (pp. 159–200). The National Academies Press. 5 Programs and Supports for Family Caregivers of Older Adults | Families Caring for an Aging America | The National Academies Press

Service	General Service Description	Service Gap Comparison	Relevant Florida Service Category	Potential Algorithmic Related Variables	Estimated Cost of Service Peer States
Remote Support/ Monitoring	Remote Support allows an off-site direct service provider to monitor and respond to a person's health, safety, and other needs using live communication, while offering the person more independence in their home. Remote Support uses two-way communication in real time, just like Skype or FaceTime, so a person can communicate with their providers when they need them. A person can choose different supports like sensors that call for help if someone has fallen or cameras that help monitor who is visiting a person's home. This service is combined with Assistive Technology.	Remote support/monitoring is a service currently supported through the iBudget. Based on the service description, it does not cover additional technologies (i.e., cameras outside the home) outside of Personal Emergency Response Systems.	Supplies and Equipment	Q23	**Ohio:** Unpaid Backup: $8.99/Hour Paid Backup: $13.99/Hour Consultation: ~$137.44 (based on outcomes) Device and Service: $75/Month (per device)

Service Effectiveness: Remote monitoring supports independence and choice by allowing people with disabilities to live more independently in their homes.[12,13] The use of these services have reported positive outcomes, including greater autonomy, ability to make decisions without in-person support, and remaining in the community longer. In Ohio specifically, the remote support services allow 24/7 monitoring which limits intrusive staff visits, supporting self-directed schedules for adults. Additionally, remote support can reduce the need for in-person staffing, which may lower per-person service costs while still maintaining oversight, although empirical cost-comparison evidence is limited.[10,14]

[12] Friedman, C., & Rizzolo, M. C. (2013). Electronic video monitoring in Medicaid home and community-based services waivers for people with intellectual and developmental disabilities. *Journal of Policy and Practice in Intellectual Disabilities*, 10(1), 1–8. https://doi.org/10.1111/jppi.12008
[13] Tanis, E. S. (2023). Expanding the use of remote supports for people with intellectual and developmental disabilities. *Nisonger Center White Paper*. The Ohio State University. Retrieved from https://nisonger.osu.edu/wp-content/uploads/2023/03/expanding-the-use-of-remote-supports-whitepaper.pdf
[14] Clausen, M. (2023, June 27). *Remote supports for people with disabilities*. The Council on Quality and Leadership. Retrieved from https://www.c-q-l.org/resources/newsletters/remote-supports-for-people-with-disabilities/

Service	General Service Description	Service Gap Comparison	Relevant Florida Service Category	Potential Algorithmic Related Variables	Estimated Cost of Service Peer States
Peer Mentorship	Peer Mentorship is support provided by peers to promote self-advocacy and encourage community living among the disabled population. The goal of this service is to instruct and advise on issues and topics related to community living. In Colorado a peer mentor is not someone that is a part of the same program or service location as the person receiving the service.	This service is used for training purposes but is not currently offered to clients in Florida through the iBudget program. Peer mentorship programs are utilized through the Department of Children and Families. This may serve as a potential model for APD service category in the iBudget program. Peer mentorship is SAN eligible.	Life Skills Development	N/A	**Colorado:** $26.04/Hour

Service	General Service Description	Service Gap Comparison	Relevant Florida Service Category	Potential Algorithmic Related Variables	Estimated Cost of Service Peer States
Service Effectiveness: Peer mentoring is effective for people with disabilities, enhancing social-emotional well-being by reducing isolation and stigma, while improving life skills like self-advocacy and decision-making. Peer mentorship programs are most successful when rehabilitation professionals and peer mentors collaborate to provide structured program activities and interventions that are meaningful and engaging for participants.[15] Evidence suggests that mentorship programs may be effective for helping youth with disabilities transition to post-secondary education or employment.[16] Mentoring was found to have a significant and positive impact; youth with LD/ADHD exhibited significantly more impairments in self-esteem, interpersonal relations, and depression without mentoring over the semester of an academic year.[17] Changes in self-esteem and depression were related to mentee-perceived mentorship quality, and appeared to be significant regardless of gender, age, family affluence, and relationship with parents.[18] Perceived quality of the mentoring relationship, and not just the mentoring content, is important in the mentoring impact, which reinforces the need for adequate training or peers. Research in the use of peer mentoring for the disabled is limited but shows promise for youths and students with conditions such as ADHD and other mental health challenges.					

[15] Ehrlich-Jones LS, Crown DS, Tomazin SE, Wong J, Kallish N, Wafford QE, Heinemann AW. Use and benefits of peer mentoring in support of employment for persons with physical disabilities: a systematic review. Disability and Rehabilitation. 2025 Sep;47(19):4896-4903. https://pubmed.ncbi.nlm.nih.gov/40265265/

[16] Lindsay S, R Hartman L, Fellin M. A systematic review of mentorship programs to facilitate transition to post-secondary education and employment for youth and young adults with disabilities. Disability and Rehabilitation. 2016 Jul;38(14):1329-49. https://pubmed.ncbi.nlm.nih.gov/26497325/

[17] Haft SL, Chen T, Leblanc C, Tencza F, Hoeft F. Impact of mentoring on socio-emotional and mental health outcomes of youth with learning disabilities and attention-deficit hyperactivity disorder. Child Adolescent Mental Health. 2019 Nov;24(4):318-328. https://pmc.ncbi.nlm.nih.gov/articles/PMC6812582/#S21

[18] Haft SL, Chen T, Leblanc C, Tencza F, Hoeft F. Impact of mentoring on socio-emotional and mental health outcomes of youth with learning disabilities and attention-deficit hyperactivity disorder. Child Adolescent Mental Health. 2019 Nov;24(4):318-328. https://pmc.ncbi.nlm.nih.gov/articles/PMC6812582/#S21

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State of Florida

Algorithm Impact Analysis

Florida Agency for Persons with Disabilities

2025 iBudget Algorithm Study

October 17, 2025

Deliverable 5 - Algorithm Impact Analysis

6 Impact Analysis

The impact analysis describes potential effects of the recommended algorithm, Model 9 – Random Forest, on the iBudget system, including its funding at the individual level, the statewide iBudget System budget, policy and procedure impacts, and other implementation considerations. This information is critical to ensure understanding of the algorithm's value to the iBudget system and its clients, as well as any unintended consequences that may arise.

6.1 Supplemental Funding Needs by Individual Category

Note: This comparison considers Model 0 (which is Model 5b with current costing information) compared to Model 9.

Model 9, Random Forest, produces individual budget amounts that are more reflective of the current needs of clients, which results in budgets that are different from current allocations, either an increase or a decrease in their original allocation. These changes were analyzed and are presented by the number of waiver enrollees whose budgets are estimated to increase or decrease, categorized by:

- Age range
- Living setting
- Current total individual budget amount

6.2 iBudget System Funding

The actual cost for the iBudget system is $1,680,682,854, which is the sum of services provided in FY 24-25 according to the APD database. The estimated supplemental funding needs are compared to the current cost and defined as follows:

- **Total Actual Cost:** The sum of all observed expenditures in the historical dataset for the base year. This represents APD's actual fiscal outlay for waiver services and serves as the empirical baseline ($1,680,682,854).
- **Total Predicted Cost:** The sum of the model's estimated allocations for each individual, based solely on assessed need and model parameters. This reflects the theoretical distribution of funds if the predictive algorithm were implemented without any legal or policy constraints.
- **Total Maximum Cost:** This measure enforces statutory protections against reductions in individual allocations by setting each person's projected cost to the greater of the actual and predicted values. The Total Maximum Cost therefore, guarantees that no participant receives less than their current level of support, ensuring compliance with legislative requirements, including section 393.0662, FS.

Table 5: Total iBudget System Funding, presents a comprehensive comparison of all models relative to actual costs. This comparison reveals each model's predictive accuracy and its implications for budget allocation. Based on the predicted maximum cost, Model 9 would require an additional $266,943,053 (15.9%) compared to the actual current costs.

Table 5: Total iBudget System Funding

Model	Predicted Cost	Percent Difference from Actual Cost	Predicted Maximum Cost	Percent Difference from Actual Cost
Model 0 (5b)	$1,375,473,878	-18.2%	$2,051,817,703	22.1%
Model 9	$1,579,418,490	-6.0%	$1,947,625,907	15.9%

Model 9, Random Forest, produces individual budget amounts that are more reflective of the current needs of clients, which results in budgets that are different from current allocations, either an increase or a decrease in their original allocation. These changes were analyzed and are presented by the number of waiver enrollees whose budgets are estimated to increase or decrease, categorized by:

- Age range
- Living setting
- Current total individual budget amount

Tables 6, 7, and 8 quantify the expected changes in budget allocations across different enrollee demographics from the current state algorithm, Model 0, to the recommended state, Model 9.

Table 6: Estimated Budget Changes

	Enrollees Whose Budgets are Estimated to Increase or Decrease	
Type of Change	**Number**	**Percent**
Decrease*	14,016	~39.5%
Increase	21,106	~59.5%
No Change	322	~0.9%

*The projected budget estimate displayed in Table 5 is defined as the maximum of the actual cost or predicted cost for each case, meaning that if a client's budget is estimated to decrease with Model 9, their actual allocation will remain the same. Individual budgets will not be reduced as the services funded have already been approved based on medical necessity.

Table 7: Estimated Budget Change by Age Category

		Model 0 (Current State)	Model 9 (Random Forest Recommendation)		
Age Groups	**Population Size**	**Average Allocation**	**Average Allocation**	**Allocation Change**	**Percent Change**
3-20	3,119	$23,003	$23,499	+$496	+2.2%
21-30	9,360	$36,748	$44,680	+$7,932	+21.6%
31 and Over	22,965	$41,793	$47,373	+$5,580	+13.4%

Table 8: Estimated Budget Changes by Living Setting

		Model 0 (Current State)	Model 9 (Random Forest Recommendation)		
Living Setting	**Population Size**	**Average Allocation**	**Average Allocation**	**Allocation Change**	**Percent Change**
Family Home	19,848	$23,547	$22,527	-$1,020	-4.3%
Independent/ Supported Living	4546	$40,756	$46,176	+$5,420	+13.3%
Residential Habilitation 1	9,297	$54,674	$85,639	+$30,964	+56.6%
Residential Habilitation 2	170	$69,313	$72,047	+$2,734	+3.9%
Residential Habilitation 3*	1,240	$120,071	$74,986	-$45,085	-37.5%
Residential Habilitation 4*	343	$157,016	$61,118	-$95,898	-61.1%

*The prediction of these service levels is not as well accommodated by Model 9 as the other service levels. These service levels may require clients to submit a SAN request.

6.3 Policy Impacts

In consideration of APD's potential implementation of Model 9, the analysis of the policy impacts did not reveal major roadblocks. Model 9 is compliant with the current program-implementing statute, section 393.0662, FS. It also meets the current requirements in 65G-4.0214, FAC to be interpretable through feature importance, though this section of code would need to be updated to reflect the new algorithm methodology, including procedures and requirements for recalibration of the algorithmic model.

The framework of Model 9, Random Forest, would support adjustments to the algorithm itself as policies change. Specifically, its non-parametric nature allows it to adapt to policy changes without model restructuring:

- If a new support type is introduced, simply add as a feature
- If QSI scoring changes, the model automatically adjusts to new patterns
- No need to hypothesize and test specific interaction terms

6.4 Implementation Considerations

Several factors need to be considered when evaluating the value of implementing Model 9, Random Forest, as the new algorithmic model to determine individual iBudget system amounts. These considerations include:

- Technical Requirements
- Operational Advantages

- Deployment Strategy
- Potential Risks
- Stakeholder Communication

Model Cost

The estimates of total costs for Model 9 are displayed in Table 9: Model 9 Estimated Cost Breakdown. The estimated costs serve as a general framework informed by the practical implementation of comparable systems.

Table 9: Model 9 Estimated Cost Breakdown

	Unit Cost	Hours	Total Cost
Development Cost	$250	340	$85,000.00
Implementation Cost	$250	380	$95,000.00
Training Costs	$250	260	$65,000.00
Annual Operational Costs	$250	340	$89,000.00
***Three-Year Cost of Ownership**	**$250**	**1,320**	**$500,000.00**

*This includes the annual operating cost three times.

The estimated preliminary costs associated with the development phase encompass traditional software development activities, including project management, programming, and business analysis. These efforts are directed toward designing, building, and configuring the system in alignment with functional and technical requirements.

The code was provided in the scientific report. Therefore, the estimated preliminary implementation costs include activities related to system testing, deployment, and initial configuration. This category also covers software licensing or procurement expenses, as well as the labor hours required to establish and operationalize the system.

Internal training will be provided to technical users to support successful implementation; however, external or end-user training is not included within this cost.

Following deployment, continuous system monitoring and refinement will be required to ensure optimal performance and to address any issues that may arise during operation.

Technical Requirements

The implementation of Model 9 requires more advanced tools and knowledge to manage appropriately. The high computational complexity of the model would require a sophisticated technical infrastructure. Cloud storage is recommended, as well as specific software dependencies detailed in the scientific report in Appendix Section 8.1, Scientific Report. The interpretability of results requires trained staff and the development of feature importance tools. While the model is tightly fit to the data, natural performance drift over time will degrade performance in the absence of structured, periodic retraining procedures. APD staff with the knowledge and capacity to maintain, train, and update the model would be required.

Operational Advantages

The implementation and maintenance of Model 9 as the iBudget algorithmic model would demonstrate key advantages, including:

- **Robustness:** Natural outlier handling without exclusions
- **Transparency:** Feature importance rankings provide interpretability
- **Stability:** Ensemble averaging reduces prediction volatility

Deployment Strategy

It is recommended that APD implement Model 9 in a phased approach to ensure a smooth transition from the current state of operations. This phased implementation would include the approach of parallel operation as described below.

- Infrastructure Setup (1 month): Python environment and model hosting
- Pilot Testing (2 months): 5,000 consumer subset validation
- Parallel Run (6 months): Side-by-side with Model 5b
- Training Program (3 weeks): Staff education on ensemble methods
- Phase Rollout (2 months): Regional deployment with monitoring
- Full Implementation (1 month): Statewide deployment

Potential Risks

Major changes to system processes, such as the potential change from Model 5b to Model 9, Random Forest, introduce risks that, when properly evaluated, can be mitigated during implementation and ongoing maintenance. Table 10: Potential Risks and Mitigation Strategies displays identified risks and mitigation strategies.

Table 10: Potential Risks and Mitigation Strategies

Potential Implementation Risk	Risk Description	Mitigation Strategy
Complexity Perception	Stakeholders may view the mathematical structure of Model 9 as a black box due to its complex nature	Develop clear visuals explanations and case examples for communications
Training Requirements	Staff need to understand the ensemble methods of Model 9	Create a comprehensive training program with hands-on exercises
Computational Resources	Requires more storage than linear models	Leverage cloud infrastructure for scalability
Explainability Infrastructure	Statistical tools for model implementation need a separate setup	Implement user-friendly explainability dashboard

To ensure the algorithm operates efficiently and produces reliable results, several steps are required beyond model training. While feature importance provides a high-level understanding of which variables drive predictions, interpreting individual predictions requires specialized explainability tools to avoid the “black box” narrative:

- **SHAP Values:** Quantify how much each feature contributes to a specific prediction, providing transparency at the individual level.[19]
- **PDPs:** Visualize the average effect of a feature across the dataset, helping to understand overall trends.
- **Individual Tree Paths:** Trace the exact decision path for a particular observation, offering a detailed view of the model's logic.

Implementing these explainability tools is essential not only for regulatory compliance but also for communicating results clearly to stakeholders and ensuring that the algorithm can be trusted and effectively applied in practice. Please refer to the Scientific Report in the appendix to obtain additional information, especially relating to the SHAP values.

Stakeholder Communication

Strategic and coordinated communication with key stakeholders, both internal and external, will be imperative for a successful transition from the current to future states of the iBudget algorithmic model. This would involve developing cohesive, easy-to-understand key messages that are tailored to the target audience, delivered by the proper authority, and at the time the message is needed. Key messages regarding Model 9 may include:

- For internal leadership:
  - Provides superior accuracy without arbitrary exclusions
  - Supports automatic adaptation to population changes
  - May reduce the administrative burden from appeals and SAN requests
- For external stakeholders:
  - Every client is included in the data; there is no outlier removal of low- or high-need cases
  - Provides personalized predictions based on unique individual needs
  - There are transparent explanations available for every decision it makes

[19] SHAP values provide mathematically rigorous feature attribution, transforming Model 9's ensemble predictions into transparent, dollar-scale explanations as required by F.S. 393.0662. SHAP values provide a mathematically consistent framework that decomposes each prediction into additive feature contributions. This allows directional interpretation (positive or negative impact), person-specific explanations, and explicit accounting for feature interactions, producing results that are more transparent and policy relevant for the iBudget analytical framework.

7 Next Steps

Following the submission of these deliverables, ISF will review the contents with APD and make any needed changes based on APD's consolidated feedback. The D6 Draft Legislative Report will be updated accordingly and submitted as the final D7 Legislative Report. As these items are under review, the statistical analyses will continue to be refined to present the most accurate and up-to-date information in D7 in November.

8 Appendix

8.1 Scientific Report

The document embedded below is the full scientific report of the iBudget Algorithm Study, containing all statistical analyses and coding details.

Final Scientific Reort
11.7.2025.pdf

8.2 Other States' Services

Through the other states research, ISF identified unique service offerings of each state examined. Table 11: Additional States Services Review, presents each states additional services, provides a brief description along with source information that APD may use to conduct additional research, and an evaluation of the service offerings.

Table 11: Additional States Services Review

State	Additional Service	Description	Reference
Ohio	Remote Support/Remote Monitoring	This service allows off-site direct service providers to monitor and respond to health, safety, and other needs using live communication. This service increases independence for people with disabilities. What makes Ohio unique is their offering of additional support outside of the traditional PERS system.	Ohio Department of Developmental Disabilities. (n.d.). Remote support [Web page]. Retrieved October 13, 2025, from https://dodd.ohio.gov/waivers-and-services/services/remote-support
	Ohio Shared Living	This living service is meant for individuals to live with their family members who provide at least twenty percent of their daily service/support needs.	Ohio Department of Developmental Disabilities. (n.d.). *Ohio Shared Living* [Web page]. Retrieved October 13, 2025, from https://dodd.ohio.gov/waivers-and-services/services/ohio-shared-living
Pennsylvania	LifeSharing	This living service is provided in the private home of an individual or family member where residential care is provided to one or two individuals with an intellectual disability.	Commonwealth of Pennsylvania, Department of Human Services. (n.d.). *Lifesharing* [Web page]. Retrieved October 13, 2025, from https://www.pa.gov/agencies/dhs/resources/intellectual-disabilities-autism/lifesharing
	Community Participation Support	This service provides community inclusion and skill identification and development support to increase the potential for competitive integrated employment. The service is usually provided in community locations/hubs, training facilities, ADL Centers, and vocational facilities.	Office of Developmental Programs. (2025, September 3). *ODP service descriptions* [PDF]. Pennsylvania Department of Human Services. Retrieved October 13, 2025, from https://www.hcsis.dhs.pa.gov/hcsis-ssd/custom/ODP_Service_Descriptions.pdf

State	Additional Service	Description	Reference
New York	Community Transition Services	This service is provided for individuals to help facilitate the transition from a specific provider or state-operated facility to independent, community living.	New York State Office for People With Developmental Disabilities. (2022, August 19). *Service documentation for community transition services* [Administrative directive]. Retrieved October 13, 2025, from https://opwdd.ny.gov/system/files/documents/2022/08/adm2015-02r-servicedocumentationforcommunitytransitionservices.pdf
Texas	Host Home/Companion Care	This living service is provided in a residence that is owned or leased by the service provider or the individual and cannot be owned or leased by the program provider. This service provides in home support for people with disabilities with the service provider residing in the same home. *Note: this service is not provided in a home shared by the individual and a family member*	Legal Information Institute. (n.d.). *26 Tex. Admin. Code § 263.5 – Description of HCS Program Services* [State regulation]. Retrieved October 13, 2025, from https://www.law.cornell.edu/regulations/texas/26-Tex-Admin-Code-SS-263-5
California	Family/Caregiver Training	This service was provided through the Cal Grows program offering free family and caregiver training through their website. These training courses were direct specifically for the aging population.	California Department of Aging. (2025). *Cal Grows – Providers & Partners* [Web page]. Retrieved October 13, 2025, from https://aging.ca.gov/Providers_and_Partners/Cal_Grows/
	Paid Internship Program	This service provides paid internship opportunities to people with disabilities to build vocational skills and work habits with the goal of securing future employment. The wages provided are funded by the CA regional centers.	California Department of Developmental Services. (2021, December). *Employment WG handout* [PDF]. Retrieved October 13, 2025, from http://www.dds.ca.gov/wp-content/uploads/2021/12/EmploymentWG_Handout_12132021.pdf
Michigan	Family Training & Non-Family Training	This service provides training opportunities for those with developmental disabilities to apply for family training & non-family training services.	Michigan Department of Community Health. (2025, October 1). *Medicaid Provider Manual* [PDF]. Retrieved October

State	Additional Service	Description	Reference
	Overnight Health & Safety Support	This service provides additional nursing services at various levels for overnight support to help the person with disabilities stay safely in their living space without the need for institutionalization.	13, 2025, from https://www.mdch.state.mi.us/dch-medicaid/manuals/MedicaidProviderManual.pdf
South Carolina	Adult Day Health Care Nursing	This service provides regularly scheduled outpatient care offering health and social support based on the individual's needs. This also includes transportation options and limited meal provisions.	South Carolina Department of Disabilities and Special Needs. (2022, July). IDRD Chapter 10: Adult Day Health Care Services (age 18 and over). https://ddsn.sc.gov/sites/ddsn/files/Public Documents/Intellectual%20Disability%20and%20Related%20Disabilities/IDRD%20Chapter%2010-Adult%20Day%20Health%20Care%20Services.pdf
	Adult Audiology	This service serves as an extension to audiology services included in the State plan, increasing audiology services to those over the age of 21 who are enrolled in the ID/RD Waiver.	South Carolina Department of Disabilities and Special Needs. (2023, March). *IDRD Chapter 10: Audiology Services (age 21 and over).* https://ddsn.sc.gov/sites/ddsn/files/Public Documents/Intellectual%20Disability%20and%20Related%20Disabilities/IDRD%20Chapter-10%20Audiology%20Services.pdf
	Adult Vision	This service serves as an extension to vision services included in the State plan, increasing vision services to those over the age of 21 who are enrolled in the ID/RD Waiver.	South Carolina Department of Disabilities and Special Needs. (2021, May). *IDRD Chapter 10: Adult Vision Services (age 21 and over).* https://ddsn.sc.gov/sites/ddsn/files/Public Documents/Intellectual%20Disability%20and%20Related%20Disabilities/IDRD%20Chapter%2010%20Adult%20Vision.pdf

State	Additional Service	Description	Reference
	Wellness Education Benefit	This service provides educational articles that are mailed to the participants home on a monthly basis providing actionable materials for family members to provide support. Participation in this service also maintains waiver eligibility.	Colorado Department of Health Care Policy and Financing. (2025, February 28). *WEB Frequently Asked Questions*. https://hcpf.colorado.gov/WEB-FAQ
	Peer Mentorship	This service offers peer mentorship to support self-advocacy and promote community living by sharing real-life experiences, offering guidance, and modeling successful community living and problem-solving.	Colorado Department of Health Care Policy and Financing. (n.d.). *10 CCR 2505-10 § 8.7537 – Peer Mentorship*. Retrieved October 13, 2025, from https://www.law.cornell.edu/regulations/colorado/10-CCR-2505-10-8.7537
Tennessee	Self-Direction: Individual Transportation	This service allows individuals to have more control over their transportation services and who provides them, often with support from a supports broker who acts as an agent and liaison. *Note: this service is available when public transportation is not*	Tennessee Department of Finance and Administration. (n.d.). *1915(c) Benefit Table*. Retrieved October 13, 2025, from https://www.tn.gov/content/dam/tn/tenncare/documents/1915cBenefitTable.pdf
	Home-delivered Meals	This service provides home-delivered meals to certain individuals who meet the eligibility requirements based on Tennessee's Tier System.	Tennessee Department of Finance and Administration. (n.d.). *CHOICES Member Benefit Table*. Retrieved October 13, 2025, from https://www.tn.gov/content/dam/tn/tenncare/documents/CHOICESMemberBenefitTable.pdf
Illinois	Training & Counseling for Unpaid Caregivers	This service includes training and counseling services for individuals who provide unpaid support, training, companionship, or supervision to individuals.	Illinois Department of Human Services. (n.d.). *Community Reinvestment Program Frequently Asked Questions*. Retrieved October 13, 2025, from https://www.dhs.state.il.us/page.aspx?item=144898&utm

State	Additional Service	Description	Reference
Georgia	Natural Support Training	This service provides training and education to individuals who provide unpaid support, training, companionship or supervision to Participants. These services must relate to the individual participant's needs due to his or her disability and tie to a specific goal in the Individual Service Plan.	Georgia Department of Behavioral Health and Developmental Disabilities. (n.d.). *In-home services*. Retrieved October 13, 2025, from https://dbhdd.georgia.gov/be-compassionate/home-services Georgia Department of Behavioral Health and Developmental Disabilities. (n.d.). *Fact sheet for Natural Support Training Services*. https://dbhdd.georgia.gov/document/document/natural-support-training-services/download[1]
	Host-Home Model	This living service is provided in a residence that is owned or leased by the service provider or the individual and cannot be owned or leased by the program provider. This service provides in home support for people with disabilities with the service provider residing in the same home. *Note: this service is not provided in a home shared by the individual and a family member*	Georgia Department of Behavioral Health and Developmental Disabilities. (n.d.). *Applications for new & existing providers*. Retrieved October 13, 2025, from https://dbhdd.georgia.gov/be-connected/applications-new-existing-providers