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How Long Does It Take to Award a Government Contract? Understanding PALT Time Frames with Big Data Analytics

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How Long Does It Take to Award a Government Contract? Understanding PALT Time Frames with Big Data Analytics

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Abstract

Awarding federal contracts is perceived as an excessively lengthy process. The purpose of this research is threefold: (1) to understand the drivers of procurement administrative lead time (PALT), (2) to identify opportunities to reduce PALT, and (3) to predict when specific requirements are likely to be awarded. These analyses will be performed using newly available, government-wide data for over 5 million federal contracts.

Keywords: Contracting, Procurement Administrative Lead Time, Big Data Analytics, PALT, Predictive Modeling, Machine Learning, Data Visualization, Time to Contract Award

Introduction

Half a trillion dollars is spent annually on government contracts that are mission critical for performing all functions of government. The vision of the acquisition system is "to deliver on a timely basis the best value product or service to the customer" (FAR 1.1020). Even in the government, time is money. The average transaction cost of a formal source selection has been estimated at $245,000 (Hawkins et al., 2016). Given the enormous quantity of contract actions across the federal government, the cost in man-hours is enormous. Of course, more time taken to award a contract usually translates to delays to internal requiring activities that rely on the work products of contractors to help meet mission needs. "Complaints of excessive PALT continue to plague the acquisition system and present challenges to both government and industry" (Berteau, 2018). The federal government is addressing procurement administrative lead time (PALT) via the President's Management Agenda. Therein, a cross-agency priority (CAP) goal called "frictionless acquisition" seeks to, among other things, deliver commercial items at the same speed as the commercial marketplace (U.S., 2021).

Nevertheless, "understanding procurement cycle time is sometimes difficult because organizational buyer behavior processes are often dynamic and complicated" (Hult, 1997, p. 403). Understanding PALT is necessary in order to muster and assign the necessary amounts and types of resources to complete required tasks. Once PALT is better understood, managing PALT is needed to reengineer processes that consume PALT and to prevent instances in which PALT exceeds reasonable bounds.

In the context of a supply chain of physical goods, the importance of procurement cycle time cannot be overstated. The government operates numerous and varied instances of such supply chains. For example, the Bureau of Engraving and Printing runs a manufacturing operation to produce currency. The military departments each operate multiple depots wherein weapon systems are overhauled and repaired. The Defense Logistics Agency serves as an inventory control point for military systems. The Department of Veterans Affairs and the military departments operate multiple hospitals and clinics that rely upon the availability of medical supplies and operate pharmacies stocked with inventory. These supply chains rely upon proper inventory management to ensure needed supplies are on hand yet minimize inventory carrying costs. Forecast accuracy partly depends on the planning time horizon. Longer planning horizons caused by longer procurement cycles can increase forecast error resulting in either excess inventory (i.e., inventory carrying costs) or stockouts (i.e., service failures), and therefore also increase safety stock levels (LeSueur & Dale, 1997). Longer lead times also result in larger cycle stock.

Despite early calls by scholars and business leaders in procurement (now referred to as supply management) in forums such as the (then) Center for Advanced Purchasing Studies (CAPS) to reduce procurement transaction costs and purchasing cycle time (Carter & Narasimhan, 1996), little progress has been made in the federal sector.

Some research has explored the antecedents of PALT. Significant factors have emerged such as dollar value of the contract action, type of goods and services, number of offers, number of evaluation criteria, contract type, and source selection method. However, research has been constrained by the unavailability of data at the transaction level (i.e., contract action) rendering models based on limited variables. Several potential predictors have not been explored such as: (1) the time remaining until the end of the fiscal year (i.e., funds availability time), (2) type of set-aside program, (3) orders against existing contracts (i.e., solicitation procedures), (4) interagency contracting, (5) buyer workload, (6) requirements returned to requiring activities (due to omissions, errors, or unresolved issues), (7) type of appropriation (i.e., one-year versus multiple-year funds), (8) buying agency, (9) buying activity, (10) option periods or quantities, (11) number of contract line items, (12) government furnished property, (13) narrative description, (14) contract consolidation or bundling, (15) the formality and rigor of trade-offs applied to task order awards, (16) combined synopsis/solicitations, and mandatory sources of supply (e.g., Ability One and FPI), to name a few. Several models have also been based on small sample sizes with low statistical power. Furthermore, models have been developed in limited contexts such as a few buying activities of only one federal agency. Research also rarely reports a comparison of adjusted R^2 to predicted R^2 and fails to report prediction intervals; thus, we don’t know how accurate the estimated models are.

When contracts will be awarded is of significant interest to contracting officers, program offices, and vendors alike. The date a requisition turns into a signed contract is the culmination of the pre-award acquisition process. FAR 7.105 emphasizes the importance of identifying schedule “constraints,” “risks,” and identifying key “milestones” in the pre-award acquisition process on the way to contract award. Typically, acquisition plans include milestone schedules developed manually by the contracting officer. Award dates are projected without statistical rigor, and the accuracy of award date projections is rarely assessed.

Meanwhile, in federal procurement, data is increasingly collected and made available publicly. Yet this vast and numerous contract award data has not been analyzed in order to build machine learning models that can be trained and result in improved predictive accuracy. Therefore, the purpose of this research is to explore new features (i.e., predictors) of PALT and to utilize them in machine learning models to more accurately predict PALT. These predictors can then be used to generate milestone schedule estimates informing customers when their contract is likely to be awarded. The research questions are as follows:

RQ1: What are the significant unexplored features (predictors) of PALT?

RQ2: Can machine learning models be applied to reliably and accurately predict when a contract action will be awarded?

The remainder of this research is organized as follows. It begins with a review of the relevant literature surrounding PALT, both in the for-profit and not-for-profit sectors. Next, the study presents the methodologies of quantitative data collection and analysis to explore the research questions. Lastly, discussion, limitations, implications, future research directions, and conclusions are offered.

Literature Review

Factors affecting PALT in a government context have been studied, but not extensively. Several early attempts to explore PALT were conducted by graduate students at the Air Force Institute of Technology and the Naval Postgraduate School in the late 1980s and early-to-mid 1990s. However, these early studies predated the explosion of information technology and major changes in federal contracting processes such as the Federal Acquisition Streamlining Act of 1994 and the Federal Acquisition Reform Act of 1995 that instituted PALT-reducing measures such as multiple-award contracts and commercial item procedures.

MacKinnon (1992) found relationships between PALT and contract type, dollar value, and type of purchase (supply, service, or research and development) using a regression model of 559 contract awards by the Naval Air Warfare Center Weapons Division at China Lake, CA. Cost reimbursement contracts are associated with lower PALT. Additionally, contracts for research and development are awarded faster than other types of requirements. Contracts for supplies consumed more time than others (e.g., for services). Contracts for larger dollar values are associated with longer PALT. However, the extent of competition did not impact PALT. MacKinnon (1992) concluded that, due to complexity, it is difficult to accurately predict PALT.

Ng et al. (1997), in their literature review of cycle time, identified several factors associated with procurement cycle time such as electronic commerce, automated reordering, and several practices associated with supplier alliances. Most of the practices pertained to partnering with suppliers; thus, they could only apply to orders once a supplier is selected. Examples included: increased frequency of buyer review of manufacturing schedule and internal requirements, supplier TQM involvement, sharing information, just-in-time ordering, and early supplier involvement in design. In a government context, Ng et al. (1997) said practices could be implemented once a supplier is on-contract. Frequent competition and supplier switching would render these practices impractical.

Lamoureux et al. (2015) examined contract awards (n = 33) from two U.S. Air Force installations in Colorado using data manually extracted from contract files (due to the limitations of FPDS-NG data). Using Multiple Analysis of Covariance, they explored whether characteristics of the source selection were associated with PALT and with contractor performance ratings (i.e., contractor performance assessment reports—CPARs). Their definition of PALT encompassed the time from receipt of the requisition to the time of contract award. They found the number of evaluation factors and the number of offers received have a significant effect on increased PALT, accounting for 62.7% of the variance in PALT. The source selection method (i.e., low-price, technically acceptable versus full trade-off) and the number of internal reviews did not affect PALT.

Landale et al. (2017) also explored predictors of PALT and contractor performance. Notably, PALT, in this study, encompassed the time from receipt of a requirement in contracting to contract award. Using a sample of 124 U.S. Air Force and U.S. Navy contracts and controlling for the effect of dollar value, PALT was found to be positively related to the number of offers and to the number of evaluation criteria. The full trade-off source selection method was found to be a marginally significant predictor of PALT ($p < .10$) showing a moderate effect size increasing PALT. The "average [PALT] was approximately 36 percent longer for the [trade-off] supplier selection method than for source selections using an LPTA approach" (Landale et al., 2017, p. 60). Also, the research revealed that an increase of one evaluation factor increased PALT by 28%. Furthermore, the study found that a 10% increase in the number of offers resulted in a 1.9% increase in PALT.

Chung et al. (2018) explored the effects of several antecedents on PALT, but only for U.S. Air Force sole source major systems acquisitions exceeding $500 million (n = 26). Factors found to increase PALT included undefinitized contract actions (UCA) (i.e., the time to definitize a UCA such as a letter contract), the number of major subcontractors and corporate transfers, foreign military sales, and the type of weapon system acquired (bombers and fighters). Other factors decrease PALT such as award to a non-profit (for research and development efforts) and the type of goods (i.e., buying armaments). Notably, several factors had no effect on PALT including price, proposal quality (operationalized as the time of initial proposal minus the time of adequate proposal = 0), aggressiveness of the government's negotiation position (contractor proposal—government objective)/contractor proposal x 100), the number of internal approvals for price being too high, and whether cost or pricing data was available on a previous acquisition.

Some benchmark studies on procurement metrics of for-profit-sector firms provide insights as to the realm of possible PALT. Zycus's (2014) Purchase to Pay Benchmarking study (n = 450+) showed that the average time from requisition to order was 4.6 days for "simple" requirements, 14.3 days for "complex" requirements, and 13 days for "services." However, these categories were not defined; hence, it is unknown what renders a requisition simple or complex. The Center for Advance Procurement Strategy (CAPS Research, 2011) published benchmark metrics in 2011 showing average cycle times across 10 industries. They measured the time from requisition approval to purchase order for both direct goods and indirect goods. The averages for direct goods ranged from 1.52 days to 50.75 days (average 11.75 days). The averages for indirect goods ranged from 2.04 days to 12 days (average 6.36 days). These cycle times are drastically shorter than those prescribed by the various federal agencies.

While efficiency is important, having sufficient PALT is also necessary. The perceived sufficiency of planned PALT (defined as the extent to which the buyer believed he or she had enough time to conduct a proper source selection process) has been shown to improve the sufficiency of the requirement definition, which, in turn, yielded higher service quality ultimately delivered by the contractor (Hawkins et al., 2015). PALT is also important in ensuring compliance with the myriad of laws, regulations, and policies in a federal contracting context. Hawkins et al. (2014) found a positive relationship between the perceived sufficiency of PALT and the perceived level of compliance of contracts. Having sufficient PALT has also been associated with bid protests. A study by Hawkins et al. (2016) showed that sufficient planned PALT reduced the fear of a bid protest. Fear of protest, in turn, increases added PALT (Hawkins et al., 2016).

Methodology

Multiple data sets were analyzed. Contract award data for all federal agencies from the USASpending.gov was used to better understand actual PALT. Newly available government-wide data on PALT time frames provides a large dataset that can be explored for answers to the research questions. PALT data collection in FPDS-NG began in Fiscal Year (FY) 2018. A total of more than 5 million contract actions were compiled for analysis covering the time period from FY2018 to FY2020. The OFPP recently declared its formal definition of PALT as a response to a requirement of Section 878 of the National Defense Authorization Act for 2019, Public Law 115–232. The OFPP's definition of PALT measures a subset of the overall acquisition life cycle, including only "the time between the date on which an initial solicitation or a contract or order is issued by a Federal department or agency and the date of the award of the contract or order" (Wooten, 2020, p. 3429).

Separately, data on shopping carts (i.e., requisitions) from the IRS's Procurement for the Public Sector (PPS) system were also used to construct a prediction model of acquisition lead time, given the minimal characteristics of the requirement known prior to transmission to a contracting activity (dollar amount, workload of assigned contract specialist, and days remaining in the fiscal year).

The remainder of the methodology is organized as follows. First, we describe the method used for the explanatory model. Next, we describe how NLP of the contract award description data was used to enhance the explanatory model. Finally, we describe the shopping cart prediction model.

Explaining PALT with USA Spending Data

We look to explain the number of PALT days using variables available in the USASpending.gov data. We identified 11 data fields present among the data that are relevant to PALT: days remaining in the FY, month of solicitation, number of offers received, NAICS code, dollar value (base plus options), civilian agency, parent award type, small business or other status, solicitation procedure, type of contract, and assisted acquisition.

The scope of the analysis omits contract modifications. The data included contract actions awarded in FY2020. In total, a random sample of 50,000 contract action awards were included. We applied a Random Forest regression model (provided through the randomForest R package) due to its ease of use and performance over other models. Random Forest models are trained using three as the ‘mtry,’ the number of predictors randomly sampled at each split when creating tree models. All other hyperparameters use default values.

Natural Language Processing of USA Spending Contract Award Description Field

The award description field is one of the few fields in USASpending.gov data that provides contextual information about what service or product is being procured. These descriptions can be key in defining the scope of work, nature of product, or complexity of service that is being procured. To limit the scope, only data on service contracts was analyzed. This analysis explored whether descriptions which are similar in context or share similar words will likely define similar scopes of work and therefore have similar PALT times.

First, re-interpreting the text data was necessary. The chosen method was through text pre-processing, vectorization, Latent Dirichlet Allocation Analysis, and token analysis. We re-interpreted the data in a machine-passable way. This is the role of text preprocessing. In this stage, we simplified the text data. The text preprocessing techniques involved trimming out non-alpha characters, ensuring all documents were entirely lowercase, removing stop-words (i.e., removing: infrequent words fewer than 250 occurrences, highly frequent words with higher than a 25% prevalence, and non-indicative words), and stemming (i.e., reducing words down to their stem). Using the text2vec library, there are two stages for pre-processing. The first is simply called “preprocessing” and it applies a string manipulation function to each entry. Then, the following “tokenization” step applies a string manipulation function to each word in each entry. The resulting tokens are the most common word-stems.

The encodings that we used to indicate whether an award contains a particular token is similar to a one-hot-encoding. Each of the tokens found in the dataset, of which there are 564, becomes a column. Then for each award row, the value in that column indicates how many times the token appears in the award description.

Then, we constructed a generalized linear model (GLM) to assess the “importance” of each token for predicting PALT. The GLM provided coefficients (weights) for the various token columns, and we can assess these coefficients to see whether a token indicates an increase or a decrease in PALT times based on whether it is positive or negative. Table 1 displays a list of the 10 highest importance tokens from a GLM. It includes their coefficients from the linear model to allow investigation of which tokens have positive or negative weightings. The Variance Importance column helps to indicate how “important” a variable is for predicting PALT. In order to get a better idea of how different tokens affect the PALT of a contract action, we use the mean PALT days for all awards that contain that token.

Table 1. Token Importance

Token	Count	Coefficient	Variance Importance	Mean PALT Days
idiq	3452	25.8	12.6	137.4
tuition	736	-90.2	11.2	9.4
macc	443	147.0	28.1	286.2
ae	1963	18.4	7.1	119.3
protect	895	45.2	12.1	143.9
guarante	660	-58.6	7.6	196.8
uss	1563	-35.2	9.7	38.2
repair	9240	-12.4	9.8	70.5
report	1545	27.7	8.4	178.4
express	740	132.2	23.8	266.0

To conduct topic analysis, we used an algorithm called Latent Dirichlet Allocation (LDA). It essentially looks at each document and creates a set of N topics based on the co-occurrences of words. For example, if the words *mechanic* and *vehicle* often end up in the same award description, they are likely to be grouped together once the LDA has been run. In this case, we are defining N = 10. This value can be manipulated based on the analysts' initial belief of the number of underlying topics. In our case, 10 topics yielded the best results.

In this visualization (Figure 1), on the right we can see the "salience" of each term; salience is the extent a term is about this specific topic. These are the terms that appear the most frequently in concurrence with other words. As shown, the words *base* and *task* are near the top where we expect them to be. The hope is that we can create a distribution for each award, where we can see the likelihood that it belongs to each cluster. That likelihood, we hypothesize, will help in grouping similar awards and hopefully with predicting PALT.

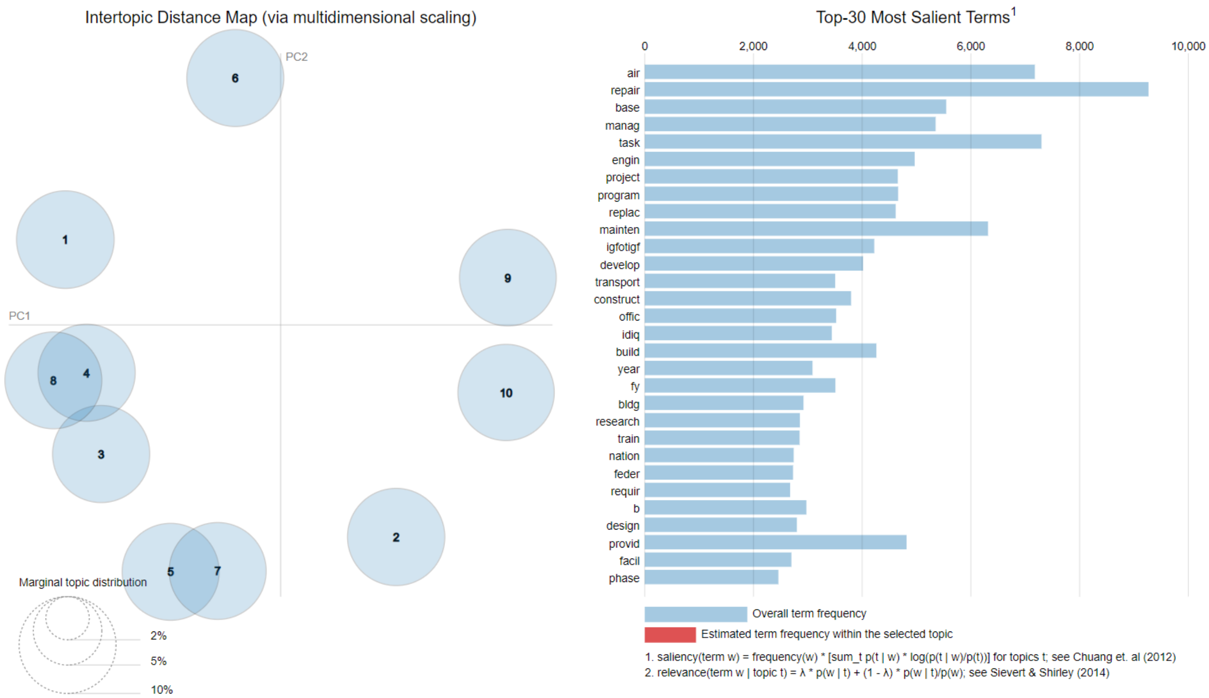


Figure 1. Topic Salience

Table 2 represents the topic distributions. Each row represents an award, and the columns indicate the likelihood for each topic. For example, the V1 column contains likelihoods of an award belonging to topic 1. Now, we can pass these into a GLM and assess the value of using these topic distributions to predict PALT.

Table 2. Topic Distributions.

	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10
1	0.000000000	0.00000000	0.00000000	0.000000000	0.00000000	0.000000000	1.00000000	0.00000000	0.000000000	0.000000000
2	0.000000000	0.00000000	0.02500000	0.000000000	0.00000000	0.500000000	0.12500000	0.00000000	0.225000000	0.125000000
3	0.000000000	0.00000000	0.00000000	0.000000000	0.00000000	0.000000000	0.00000000	0.00000000	1.000000000	0.000000000
4	0.100000000	0.00000000	0.60000000	0.000000000	0.00000000	0.000000000	0.00000000	0.00000000	0.000000000	0.300000000
5	0.000000000	0.00000000	0.00000000	0.000000000	0.50000000	0.000000000	0.00000000	0.00000000	0.000000000	0.500000000
6	0.000000000	0.33333333	0.03333333	0.000000000	0.00000000	0.300000000	0.00000000	0.33333333	0.000000000	0.000000000
7	0.000000000	0.00000000	0.00000000	0.000000000	0.00000000	0.000000000	0.00000000	0.05000000	0.950000000	0.000000000

The results of the GLM analysis are shown in Table 3. In this table, the Topic column is our interpretation of what a topic might be, based on some of the most salient words provided by the LDA.

Table 3. GLM Analysis of Topics

Topic	Sample Salient Words	Coefficient	Variance Importance
1. Planning and Logistics	Nation, require, plan, study, logistic, assess	78.712	39.0
2. Program Development and Management	Program, manage, develop, office, technical	22.614	11.4
3. Base Awards	Base, year, phase, period, idiq	22.423	10.5
4. Facility Operations	Center, operate, engine, train, facility	24.069	12.8
5. Equipment	Provide, install, medic, labor, equip	-4.9642	2.5
6. Construction and Project Design	Project, construct, design, integrate	4.7078	2.2
7. Construction	Repair, replace, build, water, roof	25.467	13.2
8. New Task Orders	Task, purpose, new, report, nurse, bpa	-10.221	5.2
9. Transportation and Maintenance	Air, igfotigf, transport, repair, test	64.491	32.3
10. General Maintenance	Maintenance, federal, software, supplies	-10.756	6.0

Predicting Contract Award Dates with IRS Shopping Cart Model

We look to predict the number of days until award for a new contract action. Rather than PALT, this model considers the time from the approval of a requisition (i.e., a shopping cart) to contract award, since the IRS dataset we are analyzing does not capture the solicitation issue date (RFX date). The scope of the analysis omits contract modifications. We ensure that contracts have a non-zero obligated value and are of the "Base Award" action type. The model is trained on all IRS obligated awards in FY2020 as of September 30, 2020. Also, the model is deliberately limited to use only data elements that are also available on a new (open) requisition. Many desirable data elements (e.g., contract type, solicitation procedures, etc.) may be unavailable or not yet decided upon early in the acquisition process.

We considered various machine learning models such as generalized linear regression and XGBoost, and settled on using a Random Forest regression model (provided through the randomForest R package) due to its ease of use and performance over the other models. Random Forest models are trained using nine as the 'mtry,' the number of predictors randomly sampled at each split when creating tree models. All other hyperparameters use default values.

We chose features based on which data fields are available in both the IRS's open and obligated ALT reports and provide information relevant to the time of shopping cart award date. We identified 12 data fields present among the data that are relevant to days in procurement. We also created four additional features from these data fields to provide the model with more data on the contract time frame and workload of the contract specialist handling the contract award. In total, the 16 features we use are as follows: Contract Specialist (CS) Section, CS.Branch, CS.Office, CS.Division, Agency, Fiscal.Year, Fund.Expiration, total_Shopping Carts (SC)_completed_at_approval, Funding.Business Unit (BU), workload_proportion, Obligated, Fund, days_until_FY_end, Functional.Area, SC.PM.Approval date, and current_CS_workload.

The four features we created evaluate the number of days until the fiscal year ends when the contract is approved (days_until_FY_end), the current number of contracts assigned to the contract specialist (CS) overseeing the contract (current_CS_workload), the total number of contracts the CS has completed in the last 90 days (total_SCs_completed_at_approval), and the proportion of their current workload to the amount they have completed in the last 90 days (workload_proportion).

Results

The data were analyzed using a combination of several methods—various data visualizations and machine learning models. Summarizing PALT by agency (see Figure 2) shows significant differences in typical time frames and the distribution of PALT for specific contract awards. The following chart sorts agencies by FY2020 PALT time frames with faster agencies appearing at the top. The top five agencies for short PALT time frames are the Small Business Administration, Department of Labor, Department of the Treasury, Department of Agriculture, and the Social Security Administration. Also notable is that the DoD reported over 173,000 and the General Services Administration reported over 126,000 PALT time frames in FY2020—a larger volume of awards than all other agencies combined.

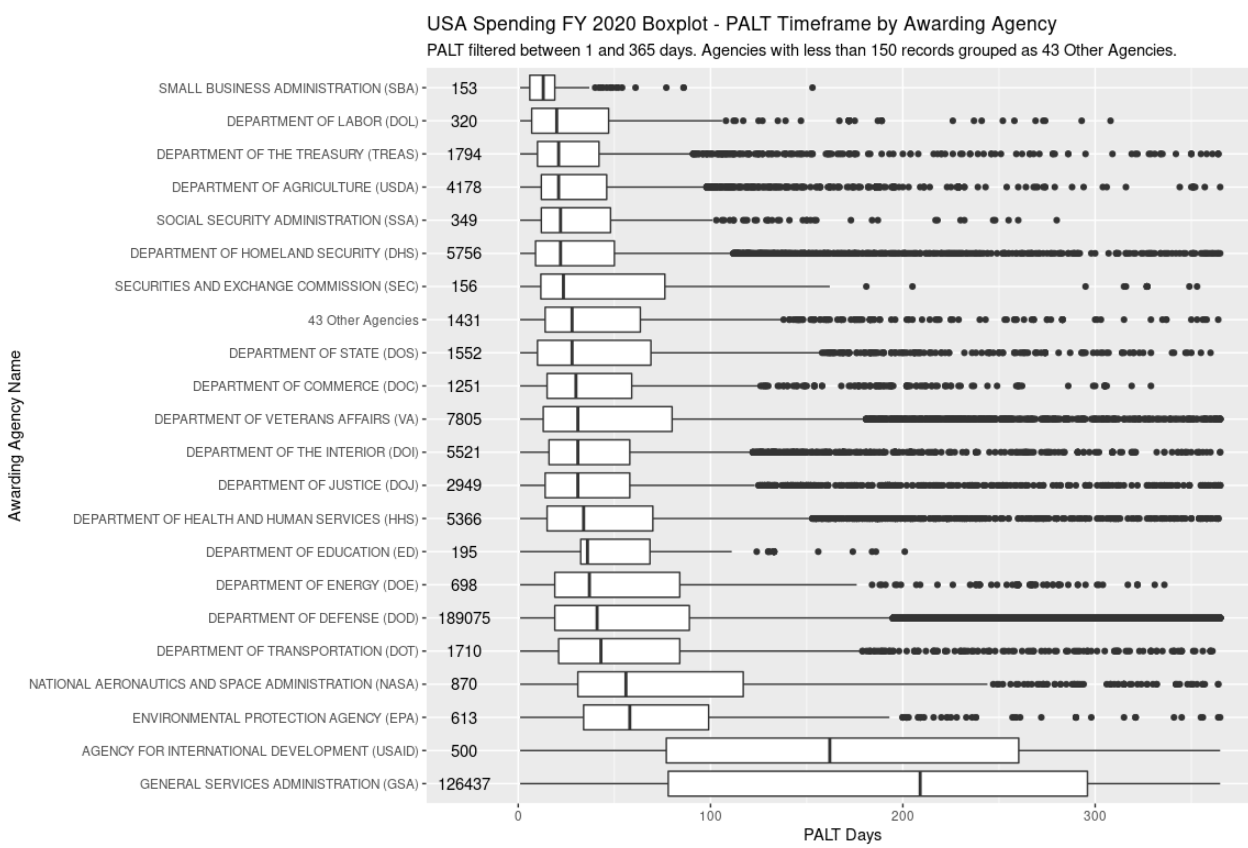


Figure 2. USA Spending FY2020 Boxplot—PALT Time Frame by Awarding Agency

USA Spending Model Explaining PALT Results

A supervised ML model (see Figure 3) was used to train the model on the data. The training data included input data and response values (i.e., PALT days). The algorithm used was a regression Random Forest model, suitable for determining quantities. Ten decision trees were used, and three variables were tried at each split.

Acquisition traits (FPDS data elements) were statistically ranked in descending order of importance as drivers of PALT time. ML models enable understanding PALT time drivers with statistical learning. The model had an explained variance of 92% and a mean of squared error of 3206.701.

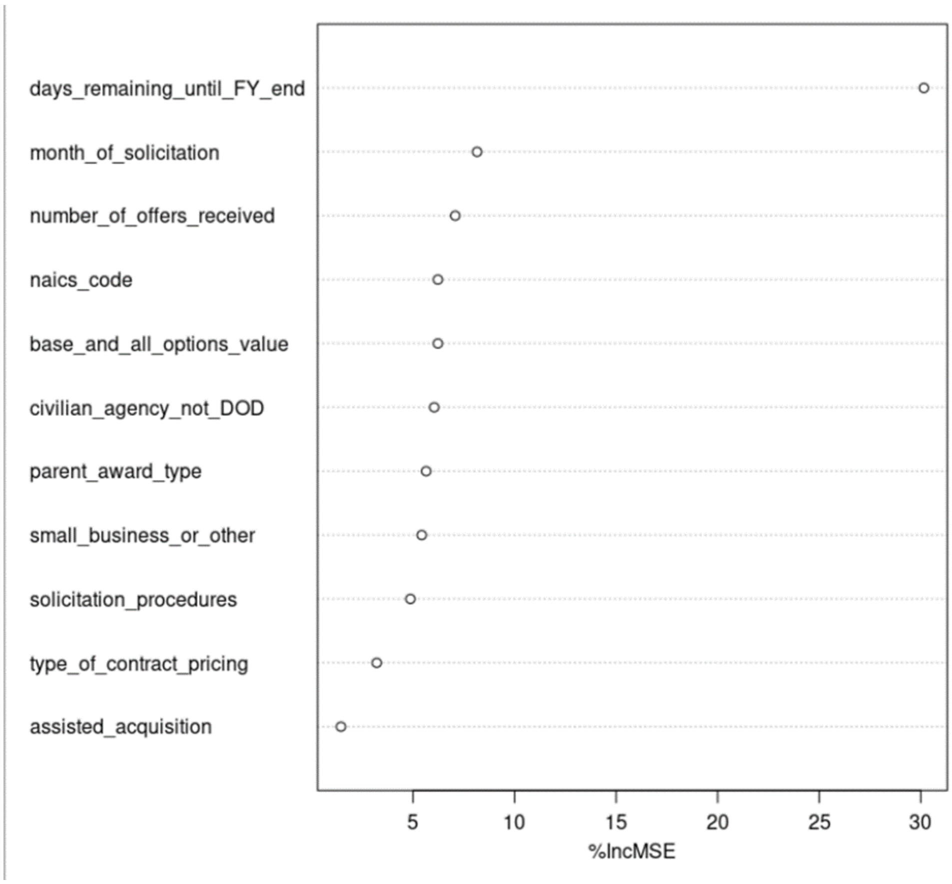


Figure 3. USA Spending PALT Explanation Model Results

USA Spending Natural Language Processing of the Contract Award Descriptions Results

In order to evaluate whether or not our encodings provide us with a more accurate PALT prediction, we appended the encodings features onto our base GLM features. Now, each award is represented by the base GLM features, as well as a series of binary columns that indicate whether or not the award contains any of the most indicative tokens in its description.

This model (see Figure 4) had an explained variance of 72.32% and a mean of squared error of 4250.511. The following table shows us that the most important feature is days_remaining_until_FY_end because it has the highest %IncMSE. This (%IncMSE) can be interpreted as the projected loss in accuracy if the feature is omitted.

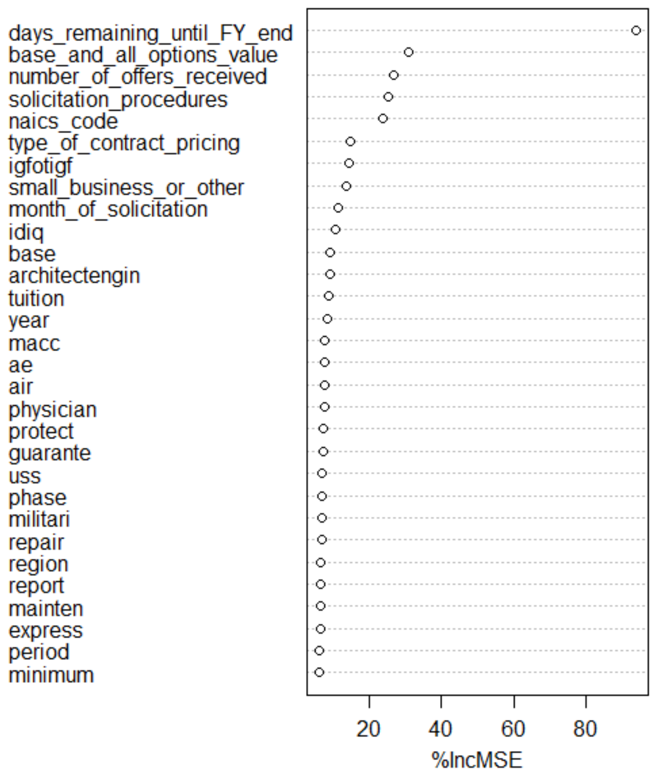


Figure 4. USA Spending Random Forest Model—NLP Encodings

The topic analysis model shown in Figure 5 had an explained variance of 69.67% and a mean squared error of 4654.5.

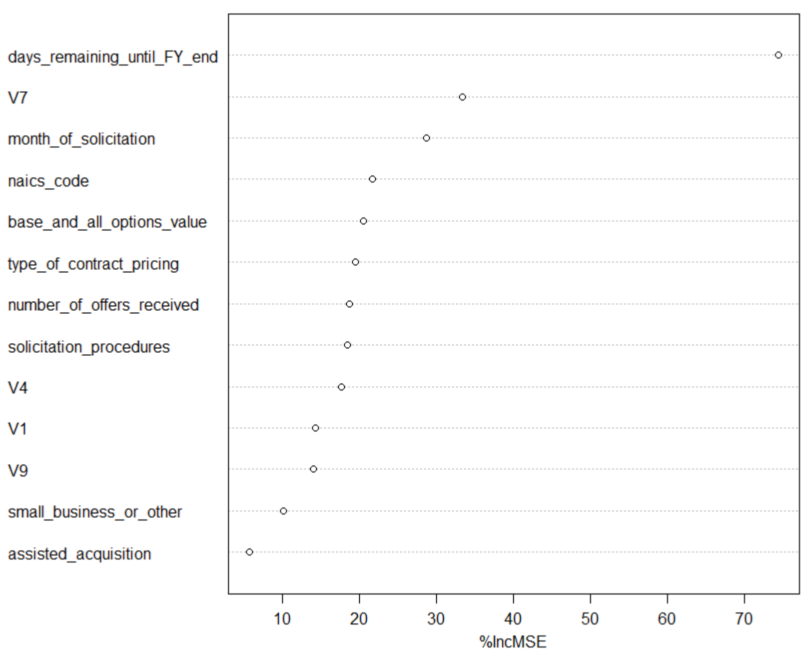


Figure 5. USA Spending Random Forest Model—NLP Topics

Figure 6 shows the token distributions of the two most informative topic features, topics 1 and 7.

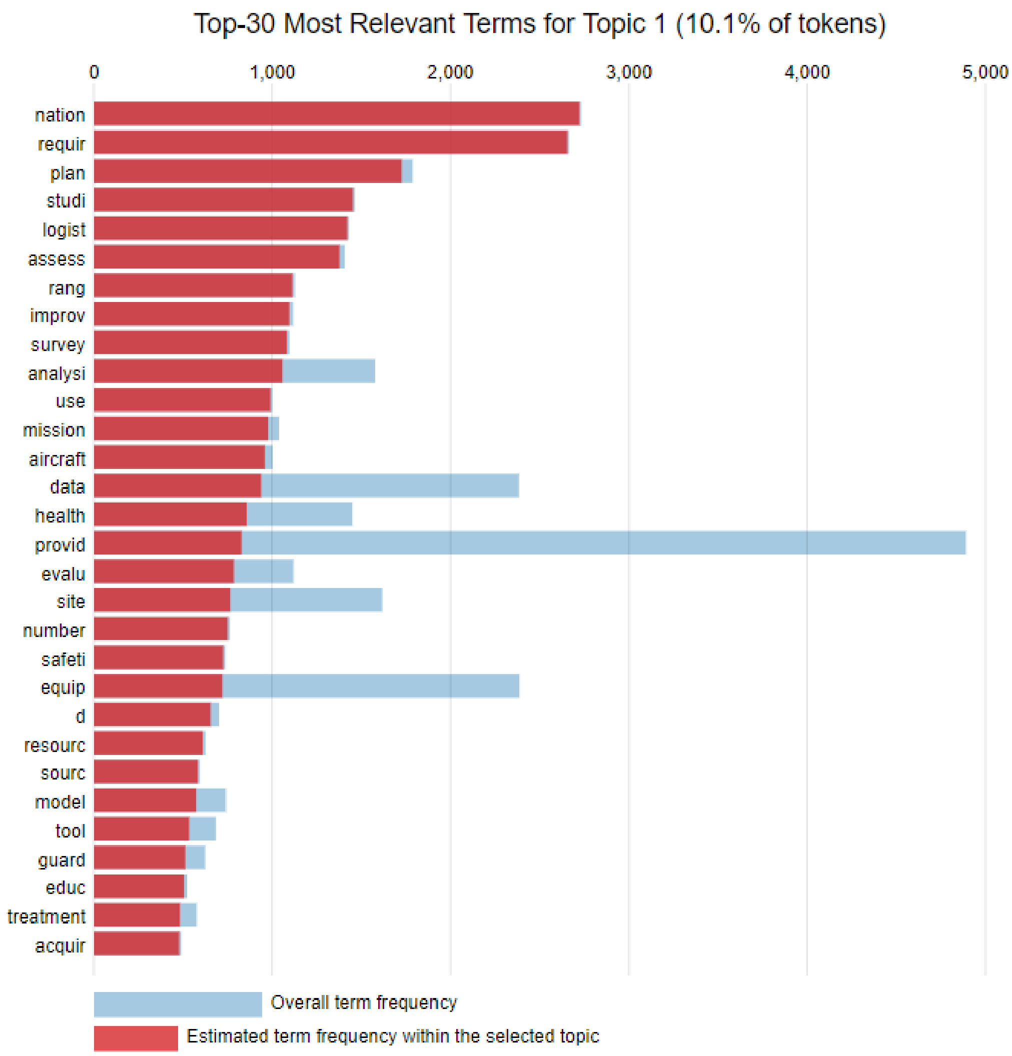


Figure 6. USA Spending—Top-30 Most Relevant NLP Terms for Topic 1

IRS Shopping Cart Model Predicting Contract Award Dates Results

When evaluating our model for feature importance, we find that the number of days until the fiscal year end (days_until_FY_end), the current number of contracts assigned to the CS overseeing the contract (current_CS_workload), and the functional area (Functional.Area) of the contract have the largest impact on model performance. The ordered list of feature importance by the percent increase in MSE when values of a feature are shuffled and the increase in node purity are plotted in Figure 7. We provide hex plots comparing the counts of the pairings of both of the continuous features and a trend line showing how the number of days of award trends with a change in value of these features in Figure 8.

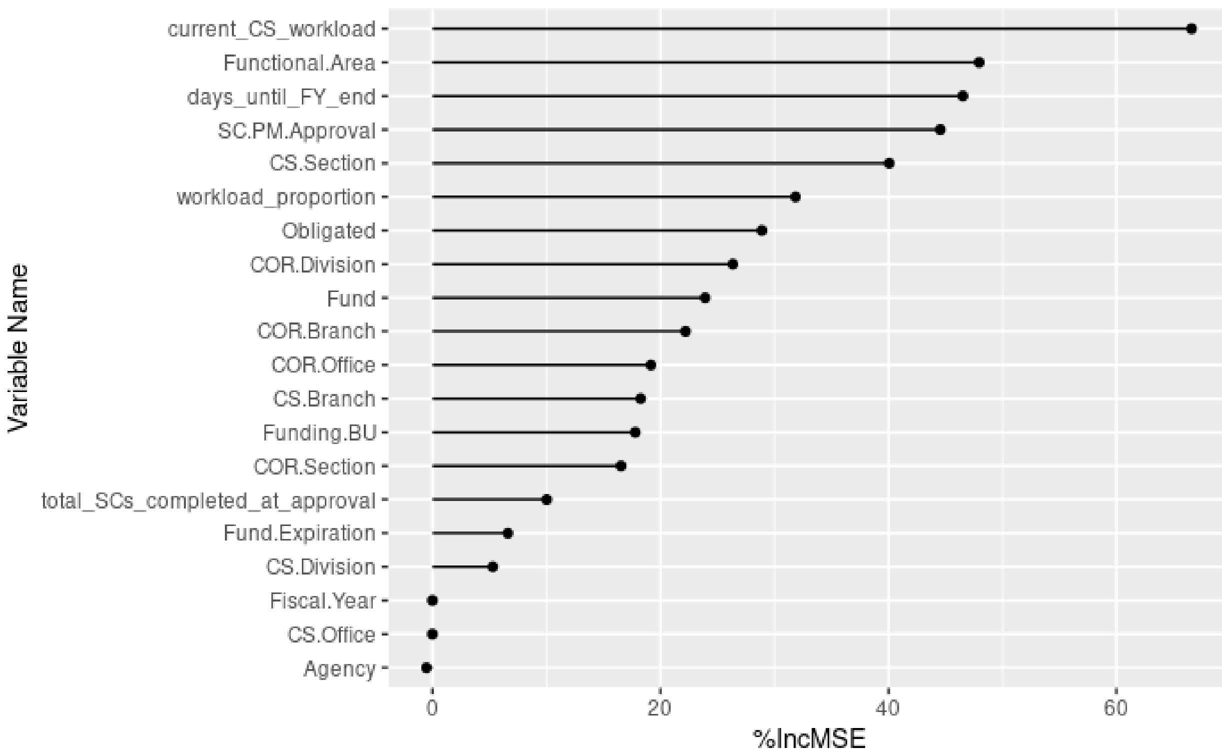
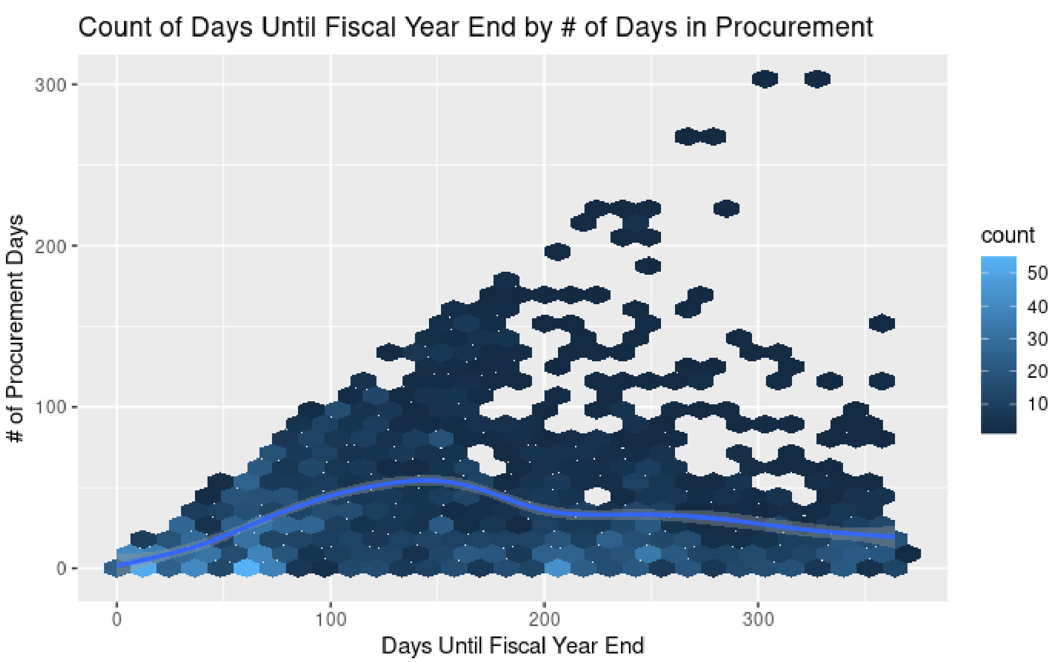


Figure 7. IRS Shopping Cart Random Forest Model



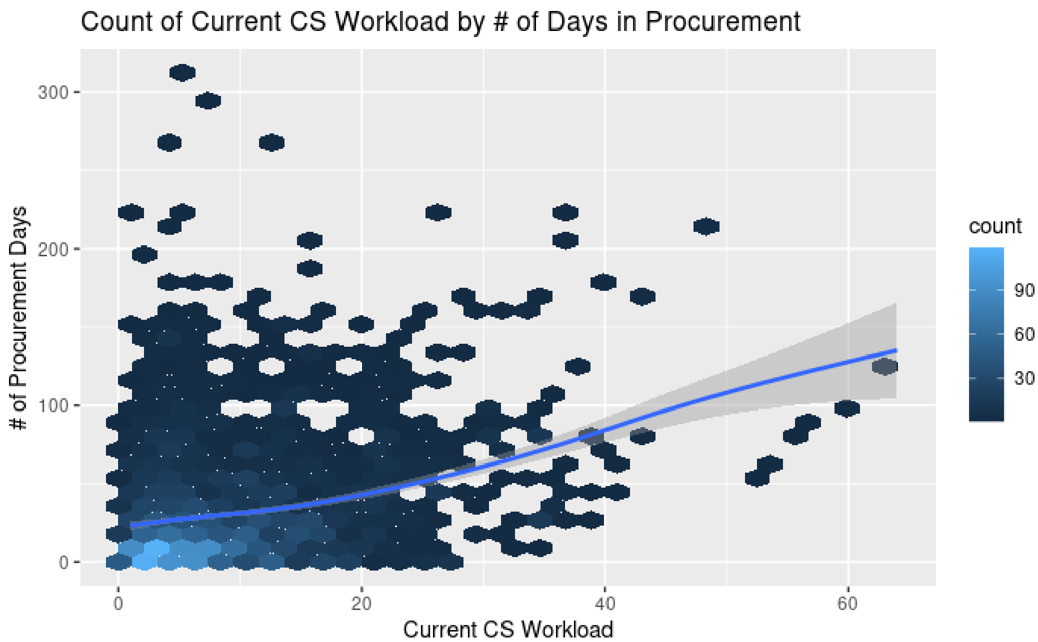


Figure 8. IRS Shopping Cart Hex Plots of Features

IRS Shopping Cart Model Evaluation and Tests of Validity

We evaluated the contract award date Random Forest model using 4-fold cross validation on the IRS's obligation PALT data sheet available in the internal September 30, 2020, PALT report. This sheet contains 2,960 observations of contract awards completed in FY2020. First, we divided these 2,960 observations into four independent subsets of 740 observations (25%) each. Then, we trained a contract award date model on each permutation of three of the four sets and evaluated their performance on the fourth test set. We report the average Mean Squared Error (MSE), Root-Mean-Squared-Error (RMSE), Mean-Absolute-Error (MAE), and R^2 value of these models in Table 4. We also provided contract prediction time frame metrics to better understand the range of time our predictions match the actual values. We provided the percent of contracts within a +/- 30-day range, same working month, a +/- 7-day range, and the same working week in Table 4. When training a model on the entire dataset, we find the out-of-bag (OOB) MSE comes to 541.9 with an R^2 value of .606.

Table 4. IRS Shopping Cart Model Evaluation

Evaluation Metric	Value		Evaluation Metric	Value
Mean Squared Error (MSE) days	571.1		Percent within +/- 30 days	86.75%
Root-Mean-Squared-Error (RMSE) days	23.8		Percent within same month	61.62%
Mean-Absolute-Error (MAE) days	14.5		Percent within +/- 7 days	44.32%
R^2	0. 563		Percent within same week	24. 19%

Discussion

Recently, government and industry leaders have expressed a need to accelerate the procurement process. Source selections consume a significant amount of time and, thus, transaction costs in terms of man-hours. Perhaps more importantly, agencies are delayed in executing their missions. Therefore, the purpose of this research was to explore new features (i.e., predictors) of PALT and to utilize them in machine learning models to more accurately predict PALT.

Several findings emerged from the analyses. First, the number of days until the fiscal year end (days_until_FY_end), the current number of contracts assigned to the Contract Specialist (CS) overseeing the contract (current_CS_workload), and the functional area (Functional.Area) of the contract have the largest impact on the PALT prediction model performance. Next, the Small Business Administration, Department of Labor, Department of the Treasury, Department of Agriculture, and Department of Homeland Security have the lowest PALTs. Several variables seem to affect the amount of PALT including days remaining in the fiscal year, obligation value, number of offers, NAICS code, solicitation procedures, and contract type. Additionally, the award date of requisitions can reasonably be predicted within the same month 61% of the time and within seven days 44% of the time. We also found that tokens that appear in the award description field in FPDS that are useful in explaining PALT included: idiq, base, architectengin, tuition, year, macc, ae, air, physician, protect, guarante, uss, phase, militari, repair, region, report, mainten, express, period, and minimum.

Lastly, useful topics included: Topic clusters V4 “Facility Operations,” V1 “Planning and Logistics, and V9 “Transportation and Maintenance,” which appear to affect PALT. Refer to Table 3 (GLM Analysis of Topics) for further information about topic clusters. Interestingly, these topic clusters usurped some characteristics of the procurement in importance (e.g., business size/type and assisted acquisition).

Managerial Implications

From the results, several recommendations for addressing PALT are made.

- Make the prediction model available to customers, enabling them to more accurately forecast needs and when those needs will be fulfilled.
- Using the results, consider adjusting the IRS’s PALT standards by redefining categories of shopping carts/requirements by solicitation procedure, competition, dollar value, and type of goods/services with commensurate PALT goals.
- Consider expanding the definition of PALT to reflect the time from the identification of the need to contract award. To do so, the date the need was identified would need to be added to FPDS-NG reporting.
- One strategy for reducing PALT is to maximize coverage of requirements by an existing IDIQ contract, basic ordering agreement (BOA; Findenstadt & Hawkins, 2015), or BPA.
- Consider how the IRS forecasts requirements in advance of need (i.e., before they get to contracting, during the customer’s budgeting process). If suppliers know the requirements well in advance, they might be able to quote/bid/offer faster. Forecasting requirements could also be useful in consolidating transactions and in ensuring an IDIQ, BOA, or BPA can cover it (i.e., in scope)—or in getting an IDIQ contract, BOA, or BPA in place.
- Evenly distribute workload to CSs so that anyone CS is not overloaded. Evaluate workload models to ensure proper staffing levels, and rebalance across organizations where necessary.
- Benchmark agencies that have lower PALT for best practices.

Study Limitations

As with any research, this study is not without limitations. The lack of solicitation dates limited the contract award actions analyzed. There could be systematic reasons for award actions not including solicitation issue dates, which would introduce bias into the results. Additionally, solicitation issue dates are only available beginning in 2018. Thus, the data is mostly limited to 2019 and 2020. Additionally, the narrow definition of PALT that excludes all of the work after the identification of a need but before the solicitation is issued omits many decisions that affect PALT (e.g., source selection method, extent of market research, contract type, etc.). Additionally, the COVID-19 pandemic in 2020 may have distorted buying patterns, such as goods and services purchased and more rapid procedures (e.g., sole source awards). Finally, data coding errors in the USA Spending data set could distort the results.

Directions for Future Research

This research raises further questions related to PALT. For example, the definition of PALT could be expanded to include all of the pre-award process from need identification to contract award. Then repeat the analyses herein to determine the factors affecting all of pre-award cycle time. Then, explore the end-to-end value chain by further examining the post-award effects of pre-award decisions. For example, what are the effects of shortened PALT on contract compliance? What are the effects of shortened PALT on post-award modifications? Does shortened PALT affect contractor performance? Additionally, for the Shopping Cart predictive model, the current contract award date Random Forest model could be extended to use training data from awarded contract data from both FY2020 and FY2021. With a larger dataset that spans fiscal years, we will look to predict on unawarded contract actions available in the open obligation PALT sheet. Finally, the NLP analysis raises opportunities to further explore the nature of the impactful topics and tokens in order to understand what is it about the appearance of terms such as “tuition” or “phase” in the award description field that either increases or decreases PALT.

Conclusion

Government and industry leaders have recently expressed a need to accelerate the procurement process. PALT was a focus of study in the 1980s and 1990s; however, emergent technology and the availability of big data provide opportunities to apply more robust methods and explore more complicated questions. Using machine learning, newly collected, standardized PALT data was analyzed to better understand factors influencing time to contract award. The goals were to explain the key factors impacting PALT, identify opportunities to increase efficiency and reduce PALT, and use a data-driven approach to generate milestone schedule estimates informing customers when their contract is likely to be awarded.

This study confirms findings from prior PALT research and also provides a more comprehensive, government-wide explanation of factors driving time to contract award. Confirmed factors affecting PALT include dollar value, number of offers received (i.e., extent of competition), the goods or services procured (i.e., NAICS code), and type of contract. A number of new insights into PALT have been quantified using a large dataset. Differences between agencies were found, with some agencies awarding contracts in a particular dollar value range faster than others. The choice of solicitation procedures by the contracting officer impacts time to contract award. Further, the number of days remaining until the fiscal year end is a powerful driver of contract award dates. The contracting personnel’s workload also affects PALT, as does the organization which they support. Finally, certain words and word-combinations in the award description field are related to PALT. A better understanding of these factors should help acquisition teams to reduce PALT and help acquisition leaders to set policies and processes to mitigate PALT.

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