ANALYSIS OF MACHINE FAILURE CODES AND THE IMPACT ON CUSTOMER SATISFACTION

by

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ABSTRACT

It is challenging to know when customers are satisfied or dissatisfied with a product or service. Feedback mechanisms such as surveys are frequently used to gain feedback and evaluate the customer's perceptions of the product or service. John Deere, like most companies, takes an active role in understanding customer satisfaction, using surveys and feedback through field teams and the dealer channel. Shortcomings with this method include the need for customers to voice their complaints first, which can take a significant amount of time, delaying John Deere from providing needed service.

The purpose of this research is to examine the usefulness of using primary diagnostic data collected by John Deere to assess customer satisfaction. Specifically, to examine if the number of diagnostic trouble codes (DTCs) on a John Deere 8R series row crop tractor experiences has an impact on customer satisfaction scores reported on surveys. Then determine if this data would be useful to help identify dissatisfied customers proactively.

Statistical analysis and regression were used to understand the impact DTC's have on customer satisfaction. Analysis indicates that for every 100 Total DTC's a machine exhibits one could expect to see a 4 point reduction in overall CSI score by the customer. This information may prove valuable in being able to understand customer satisfaction more proactively

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CHAPTER I: INTRODUCTION

The goal of a firm is to be profitable. One factor that strongly affects profits is the organization's customer base. The long term financial success of a firm can hinge on customer loyalty and repurchase intent. This is due in part by simply having a secure customer base and the fact that acquiring new customers cost more in additional resources than keeping current customers. The satisfaction a customer has when they purchase and use a good or service plays an important role in their repeat purchase decision. Meeting a customer's needs and performance expectations is important for any business to survive and be competitive. When a firm can identify customer dissatisfaction and resolve those concerns for the customer, the company can turn the customer into a potential customer for life. The ability to attract, maintain and support customers while decreasing overall costs and increasing profitability for the company is one segment of customer relationship management or CRM.

Understanding when customers are satisfied or dissatisfied with a product or service is challenging. Feedback mechanisms such as surveys are frequently used to gain feedback and evaluation of the customer's perceptions of the product or service. John Deere like most companies takes an active role in understanding customer satisfaction, using surveys and feedback through field teams and the dealer channel. Shortcomings with this method include the need for customers to voice their complaints first, which can take a significant amount of time, delaying John Deere from providing needed service.

John Deere is looking for innovative ways using technology and existing resources to discover more proactive methods of understanding and dealing with potential customer concerns that could result in customer dissatisfaction. John Deere would like to identify the feasibility of finding a solution that could identify these customers before they become dissatisfied and resolve their issues proactively versus reactively.

The purpose of this research is to examine the usefulness of using primary diagnostic data collected by John Deere to assess customer satisfaction. Specifically, to examine if the number of diagnostic trouble codes (DTCs) that a John Deere 8R series row crop tractor experiences has an impact on customer satisfaction scores reported on surveys. Then determine if this data would be useful to help identify dissatisfied customers proactively. Currently the customer satisfaction survey is administered 6 months after the delivery of the machine allowing a customer adequate time to assess machine performance through a use season. However this significantly lengthens the response time of the company to respond to product issues and does little to proactively identify customers that may become dissatisfied with their purchase.

Statistical analysis with linear regression will be used to determine statistical relationships and quantify the influence that diagnostic trouble codes exhibited by an 8R row crop tractor have on corresponding customer satisfaction. Once these factors are identified, the relationships between the factors and DTC's that the machine provides will be used to help proactively identify customers that may experience dissatisfaction, in order to resolve their issues before they become a dissatisfied customer. Specific objectives of this research are to:

- Evaluate the impact machine diagnostic trouble codes have on customer satisfaction.
- Evaluate the current customer feedback system to identify its strengths and weaknesses.

- Identify a proactive approach that targets customers that may have a reduced satisfaction score due to the number of DTC’s generated by a machine.

The problem analysis and solution development will be, to the extent possible, quantitative. Achieving the foregoing objectives will help to provide John Deere and its dealer channel a proactive approach to determine customers that could be at risk and resolve any issues for those customers, proactively. This will enhance the customer experience, satisfaction and ultimately result in higher customer retention, securing future sales for the dealer channel and John Deere.

The deliverables for this project will be in the form of a written thesis presented to the Kansas State University Master of Agribusiness program. Additionally, there will be an oral presentation made to Kansas State Master of Agribusiness committee. The final presentation will be a combination of the written thesis and oral presentation to the management at John Deere for consideration and implementation. This presentation will provide insight and recommendations regarding the opportunity to proactively identify and target customers that are potentially at risk of being dissatisfied with a product.

Data for the project will be obtained from; customer satisfaction surveys used by John Deere through their dealer channel, as well as access to machine data regarding DTC fault codes that occur on a machine. This data will be analyzed to determine the extent and degree of correlation between customer satisfaction scores and diagnostic codes exhibited by a machine and automatically reported daily. Given that machine data is gathered in near real time, this data offers an opportunity to be more proactive than current methods allow.

CHAPTER II: LITERATURE REVIEW

Customer satisfaction and its relationship with repurchase intent have been extensively researched over time. Varying methods have been used to determine customer satisfaction, as well as the impact it has for companies. This review will examine how customer satisfaction impacts customer repurchase intent, impact of firm performance, and how firms approach customer satisfaction.

Customer satisfaction is both a goal and a marketing tool (Kotler and Keller 2012). Firms should be concerned with customers' satisfaction of their products and services. A firm's success depends in part upon their customers' satisfaction and can be the difference in success or failure of a company. When assessing brand image of a firm, customer satisfaction can have a positive influence on the overall brand image as well as the value of the firm. The American Customer Satisfaction Index (ACSI), developed by the University of Michigan, measures satisfaction of consumers across the U.S. economy. ACSI produces customer satisfaction scores for more than 225 companies across 45 industries (Aksoy 2009).

Positive customer satisfaction not only has a positive impact on customers it can also increase a firm's value. For example, Aksoy (2009) found a $100 dollar investment in a portfolio of companies with high customer satisfaction over a 10 year period increased value three fold (see Table 2.1). This research demonstrates a positive correlation with increased customer satisfaction and the financial impact it has on the company's bottom line performance. This continues to drive home the importance customer satisfaction can have on a business's financial performance.

Table 2.1: Performance Differences Based on Customer Satisfaction

$100 investment in alternative stock options based on customer satisfaction	1996 (Initial Value)	2006
High Satisfaction Firms[a]	$100	$312
S&P 500	$100	$205
Low Satisfaction Firms[a]	$100	$98

Source: (Aksoy 2009)
[a]High satisfaction firms are identified as firms having above national average ACSI score and exhibited an increase over the ten year period. Low satisfaction firms are identified as firms having below national average ACSI score and decreasing trend over the ten year period.

Studies show that while customers are dissatisfied with purchases 25% of the time, only about 5% actually complain. The other 95% either feel complaining is not worth it or don't know how to or whom to complain to. Of the 5% that complain, 54 to 70% will do business again with that company if their complaint is resolved (Kotler and Keller 2012). Customers whose complaints are resolved satisfactorily will tell on average 5 people about the positive result. However the average dissatisfied customer will tell 11 people about their poor experience (Kotler and Keller 2012). Given the downside of an unhappy customer, it's critical that businesses deal with negative experiences properly.

The long term financial impact of customer satisfaction on a firm has been investigated by Mittal, et al. (2005). This study found the link between a satisfied customer and the long term performance of a company to be positive and stronger for firms that keep and improve the relationships with satisfied customers. In addition, these benefits may help to improve efficiency by reducing costs within the firm. Strong financial performance in the long-run can be achieved for firms that successfully achieve dual aims simultaneously: successfully satisfying customers and achieving efficiency gains (Mittal, et al. 2005).

Customer satisfaction and repurchase behavior can also be affected by the customer service it provides. Customer service in response to complaints or dissatisfaction has a positive and significant impact on overall satisfaction; which has a positive impact on purchase intention, which in turn has a positive impact on actual repurchase (Akhter 2010).

Curtis (2011) conducted a rigorous and comprehensive review of studies that have examined the relationship between customer loyalty and repurchase intent; loyalty and satisfaction; and repurchase intent and satisfaction in an effort to conduct a meta-analysis on the relationship linking customer satisfaction, loyalty and repurchase intent. Results found over eighty published studies that related to these topics. The meta-analysis results in Table 2.2 indicate that satisfied consumers exhibit stronger loyalty. This loyalty is positively linked to satisfaction and repurchases.

Table 2.2: Observed Correlations in Meta-Analysis

Constructs	Meta-Analysis Correlation
Loyalty-Satisfaction	0.54
Repurchase-Satisfaction	0.56*
Repurchase Intent-Satisfaction	0.63
Loyalty-Repurchase Intent	0.71

Source: (Curtis 2011) *Confidence intervals included zero

Examining Table 2.2, loyalty and satisfaction (in the top row) show a positive correlation of 0.54, indicating a positive relationship between customer loyalty and satisfaction. Looking at the bottom row in the table, the strongest correlation is found between customer loyalty and repurchase intent, which confirms the notion that loyalty and repurchase intent are positively related. Repurchase intent for a the product and improved customer satisfaction for a company can translate into future sales.

CHAPTER III: CONCEPTUAL FRAMEWORK

This chapter discusses different models and how they interact and relate to customer satisfaction and the impact it can have on the business in the form of reducing inefficiencies and improving productivity and customer satisfaction for John Deere and its customers. The first model focuses on the factors affecting customer service from John Deere's perspective and the second illustrates the process by which customers form their expectations about a company's product. Both come together to provide a framework for analyzing customer satisfaction.

The goal of a business is to be profitable. A significant factor affecting profits is the customer base. The long term financial success of a business can hinge on its customer base, customer loyalty, and the repurchase intent of those customers. Acquiring new customers can cost a company more than keeping current customers. A major factor of keeping customers is satisfaction, as it plays an important role in the repeat purchase behavior for any product. Meeting customers' needs and performance expectations is important to survive and be competitive. When a firm can identify customer dissatisfaction and resolve potential concerns for the customer, the firm can turn a customer who is dissatisfied into a potential customer for life. Understanding when customers are satisfied and dissatisfied can be a challenge however. Most firms use feedback mechanisms such as surveys or other methods after the customer is already dissatisfied. John Deere uses the same tools to understand customer satisfaction, which are based on surveys and feedback through field teams and the dealer channel. However, these methods still require customers to voice their complaints or dissatisfaction first. John Deere is looking for new innovative ways of using technology to be more proactive at understanding potential customer concerns that can result in dissatisfaction.

Value innovation is the constant and incessant recombination of resources to reduce supplier costs and increase customer value (Mauborgne and Kim 2005). In short, creating value for both the customer and the supplier results in a win/win situation. Value innovation can be achieved by proactively seeking to improve customer satisfaction with a company's products.

Customer satisfaction is an opportunity to leverage value innovation to identify ways to reduce costs to John Deere and improve customer value. This can be achieved by proactively identifying sources of customer dissatisfaction and resolving them in a timely and efficient manner, resulting in increased customer/buyer value. As a customer of John Deere, sources of dissatisfaction can be a wide range of factors. For the sake of this study we will focus on one specific model line of equipment, which is a row crop agricultural tractor. Customer satisfaction is scored by customers in the following areas: Overall satisfaction of the product, engine, transmission and warranty. These areas are scored by customers in a satisfaction survey that is sent to them after a use season so that they will have adequate experience with the product. This data will be used in the study to identify new areas for innovation through reduced costs to the company and increased customer value. Increased customer value will come from new support services provided by the dealer and John Deere.

Eliminating undesirables in the current process is another key aspect of consideration. Currently there is a lengthy wait time in determining customer satisfaction. This long lead time can be detrimental for prolonged customer dissatisfaction. Currently customer satisfaction surveys are sent after a complete use season, which is usually six months. This is for good reason, as it allows the customer adequate time to assess the operation of their product. However, this process results in a very untimely report of customer satisfaction during their peak usage if they should encounter a problem. Eliminating the length of time or ideally removing the opportunity a customer may experience dissatisfaction as a result of poor performance or machine failure could eliminate an unfavorable customer experience and further improve customer satisfaction.

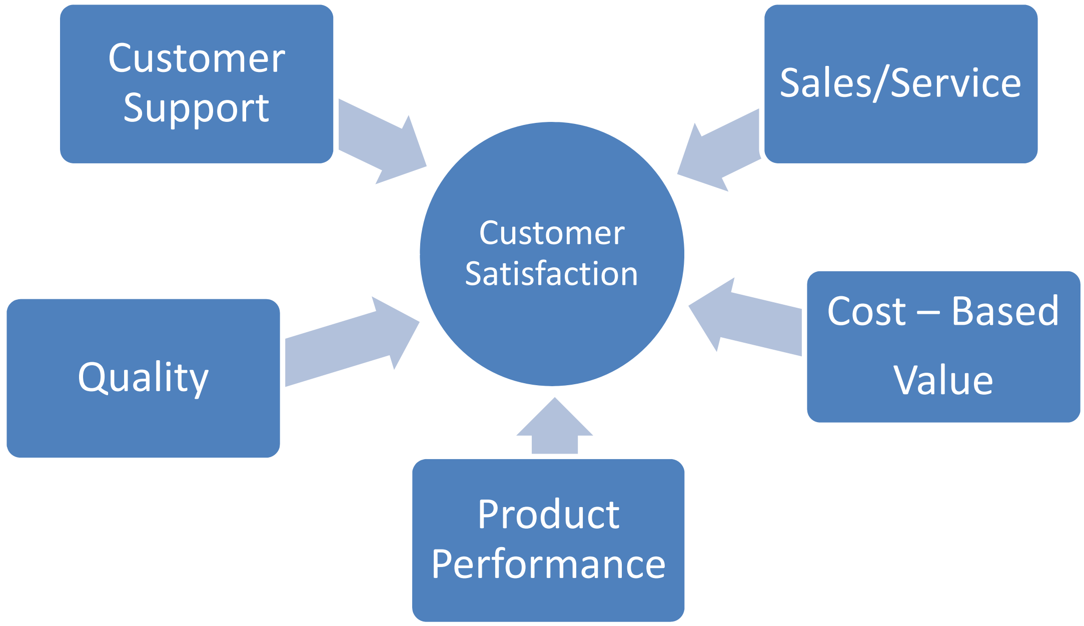
Customer satisfaction information provides a strong source of feedback to help deliver value to the customer. This value is diminished in the current surveying method as the turnaround time to receive this data is lengthy, at six months or longer, before the survey is administered and returned. The focus here is to help eliminate and reduce the current slow and limited response to customer dissatisfaction.

We can focus on increasing high value desirables such as customer satisfaction with increased speed and response to customer needs. Increasing these desirables will allow for improved customer satisfaction and awareness of potential product issues and complaints. The company can not only respond sooner to individual customers' needs, it can identify any trends and respond quicker to all customers' potential issues, which may result in dissatisfaction, as well.

Responding quicker and more proactively to potential customer dissatisfaction would lead John Deere into creating new desirables that are currently nonexistent. This opportunity would provide new value to John Deere customers by allowing a more proactive approach to customer satisfaction and problem resolution. The analysis completed in this study is focused around providing a more proactive approach to customer satisfaction allowing John Deere to improve response time (in the expectations disconfirmation model figure 3.2 discussed below). Through proactive identification of potential customers' needs and problems, John Deere can prevent dissatisfaction. This in turn eliminates undesirables, creates new value, increases satisfaction, and reduces inefficiencies for John Deere and the customer.

There are many factors that play a role in ensuring customer satisfaction as seen by John Deere (see Figure 3.1). There is product performance which includes features, functionality and the solutions the product provides for the customer. Customer satisfaction is impacted by product quality, which includes reliability; longevity and durability of the product; and the customers intended use of the product. Finally, sales and marketing along the distribution channel can play a role in establishing and meeting customer expectations that in turn result in a satisfied customer. The customer support offered by company and dealer channel as well as cost based value to the customer all impact customer satisfaction. When looking at customer satisfaction from an overall systems approach there are many parts of the system that can affect customer satisfaction.

Figure 3.1: Customer Satisfaction Used By John Deere



John Deere has a long standing reputation with customers. The company strives to provide a quality product that provides value and meets customer's performance expectations. In addition to providing a quality product, John Deere also has a strong focus on customer support that originates at the company level and is implemented at the dealer level where the dealer provides the sales and service directly to the customer.

Many different models have been used to explain customer satisfaction and extensive research has been done examining these various models. The research done by Erevelles & Leavitt (1992) provides a review of seven of these models, which are listed in Table 3.1.

Table 3.1: Satisfaction Models

1. Expectation Disconfirmation Model
2. Perceived Performance Model
3. Norms Models
4. Multiple Process Models
5. Attribution Models
6. Affective Models
7. Equity Models

(Erevelles and Leavitt 1992)

A brief explanation of each of the model types mentioned in Table 3.1 is provided below.

1. The *Expectations Disconfirmation Model* was originated by Richard Oliver (1980). This model has consumers comparing pre-purchase expectations with post-purchase experiences of a product or service. If a product outperforms expectations (positive disconfirmation) the result will be consumer satisfaction with the purchase. If the product or service fall short of expectations (negative disconfirmation) then the consumer is more likely to be dissatisfied (Oliver 1980).
2. The *Perceived Performance Model* differs from model #1 above in that expectations do not play as significant a role in determining satisfaction. This model works well when a product or service exceeds consumer’s expectations such that they discount their expectations in their post-consumption assessment of the product or service, meaning the consumer will be satisfied regardless of any disconfirmation effects (Tse and Peter 1988).
3. *Norms Models* are similar to expectation disconfirmation models. A consumer compares perceived performance with expected performance. It differs in the area

that instead of considering that actual consumption experience, the customer uses the comparison of what should happen rather than what will happen to manage their expectations (Hom 2000).

4. *Multiple Process Models* assume customer satisfaction is a multidimensional process formed when a consumer uses more than one standard of comparison when determining their confirmation/disconfirmation with a product or service (Hom 2000)

5. *Attribution Models* have predominantly been used to determine dissatisfaction. Consumers seek to rationalize the outcome of their purchase (Wong and Weiner 1981). Consumers use three factors to determine how attributions affect their satisfaction at the locus of causality, stability, and controllability. Causality can have internal or external meaning. Internal meaning occurs when the consumer is responsible for product performance and external meaning occurs when the provider is responsible for product performance. Stability means failures are seen as a rare occurrence and not normal and the consumer would be more likely to forgive the failure. If the consumer feels the provider had control over the performance or lack of performance the consumer would be unsatisfied due to the control the provider had to affect it in a better way (Hom 2000).

6. *Affective Models* differ from the other models. Instead of being based on a cognitive process to determining satisfaction, affective models are based on emotions, liking of the product and mood, which can all influence the consumption experience (Hom 2000).

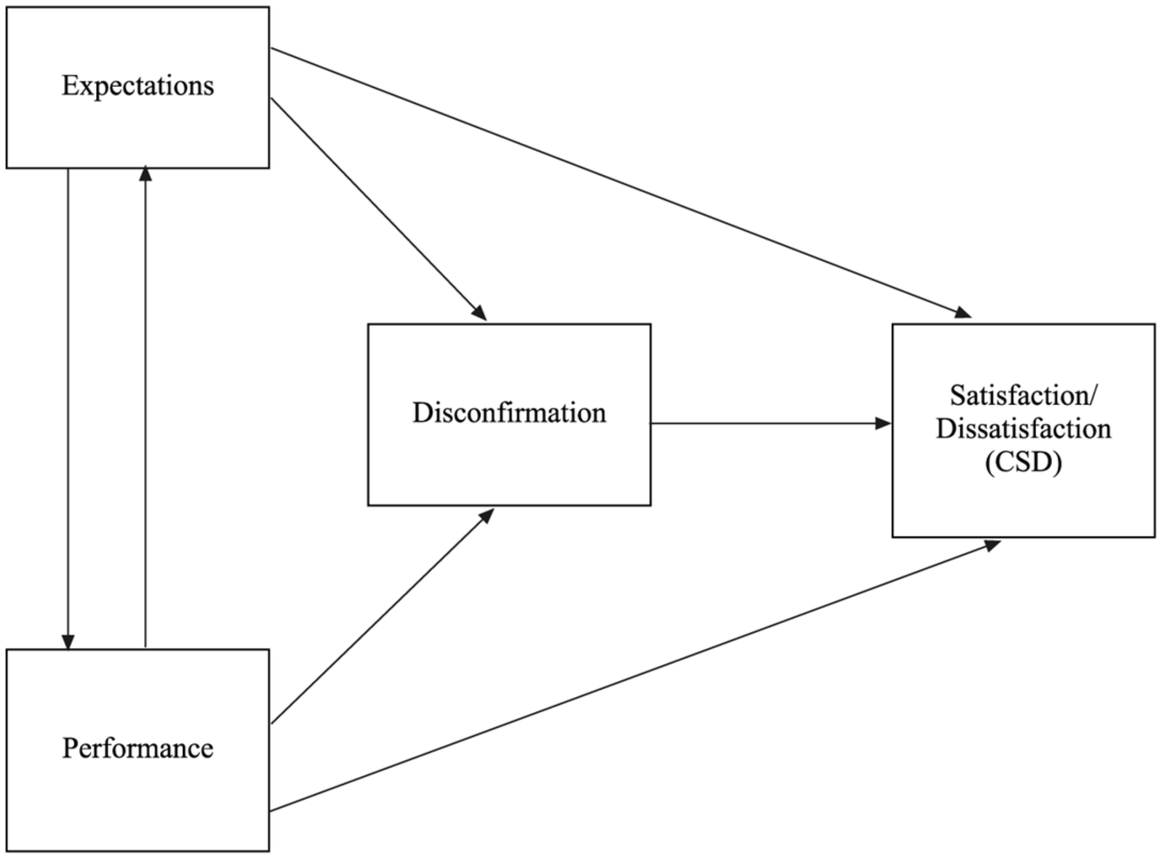
7. *Equity Models* assess the consumer's attitude about fair treatment in the consumption process. The amount of return for the investment put forth by a consumer is the ratio of equity to the amount invested and if the consumer deems this a fair transaction. This model is derived from equity theory (Stacy 1963)

While each model has its unique abilities to determine satisfaction, one model continues to be used predominantly in customer satisfaction research. This is the expectations disconfirmation model (Figure 3.2) by Richard Oliver (1980). In this model, consumers are believed to have formed an opinion of the product or service before purchasing/experiencing it. Once the consumer has experienced the product or service they then formulate their opinion based on what their pre-purchase expectations were and their actual experience is. If their experience was better than expected performance, then they would have a positive disconfirmation and are satisfied with their purchase. When the consumer's experience is less then what was expected, then there is said to be a negative disconfirmation with the result being dissatisfaction.

The expectations disconfirmation model Figure 3.2 will be adopted for the base customer satisfaction model in this research and analysis of how the customer perceives satisfaction. The expectations disconfirmation model aligns with the method our customers and John Deere use to assess product performance. Before a customer purchases a John Deere 8R row crop tractor they have a pre conceived level of expectation of the machine itself and also the service and support that comes with it from the dealer, this is seen as the expectation in Figure 3.2. Once the customer has used the product they then formulate their conclusion if it met their pre-purchase expectations. If the performance level of service has met or exceeded their expectations, then they are satisfied (positive disconfirmation), if the product performance or level of service does not meet the customer expectations (negative disconfirmation), then the customer will be dissatisfied.

The purpose of this thesis is to see if we can proactively determine when a customer might become dissatisfied. Currently the customer would need to voice their concern or dissatisfaction to their dealer or worse yet through a survey that is administered six months after they have received their machine. By being proactive John Deere or the dealer can reach out to the customer proactively through DTC monitoring. Once a certain quantity of DTC's have been generated by a machine they can reach out to the customer while the customer is in the midst of using the product to proactively resolve their concerns before the customer becomes dissatisfied, avoiding potential disconfirmation of prior expectations. This will ultimately lead to increased customer satisfaction and increased return business for the dealer and John Deere.

Figure 3.2: Expectations Disconfirmation Model



(Oliver 1980)

CHAPTER IV: METHODOLOGY

4.1 Overview

This chapter will discuss how the data analysis was conducted what data was used in the analysis. The objectives of this thesis are to use statistical analysis and linear regression to determine whether a model can be found that explains the relationship between a customer satisfaction index (CSI) and the number of diagnostic trouble codes (DTC's) generated by a machine in order to discover the effects of machines diagnostic trouble codes on customer satisfaction. The results will be used to determine if a predictive model can be used to explain customer satisfaction based on the quantity of diagnostic trouble codes exhibited by a machine.

The primary variables being used will be machine diagnostic trouble codes that have a range of three severities: red, yellow, and informational. The dependent variable being analyzed will be customer satisfaction. The following is a brief description and example of each type of DTC. Red codes are critical codes that when exhibited usually indicate a need to shut down the machine, (e.g. low engine oil pressure). Yellow codes are less critical and indicate a need for the operator to be aware, (e.g. hydraulic oil filter restricted). Informational codes are meant for operator awareness, (e.g. reverser lever not in neutral or park during startup).

Simple correlations between variables will be used as an initial analysis. Correlation analysis measures how closely two variables move together. The closer to one, the closer they move in the same direction. The closer to zero, the more the series are unrelated. The closer to -1, the closer the series move in opposite directions. (Studenmund 2011)

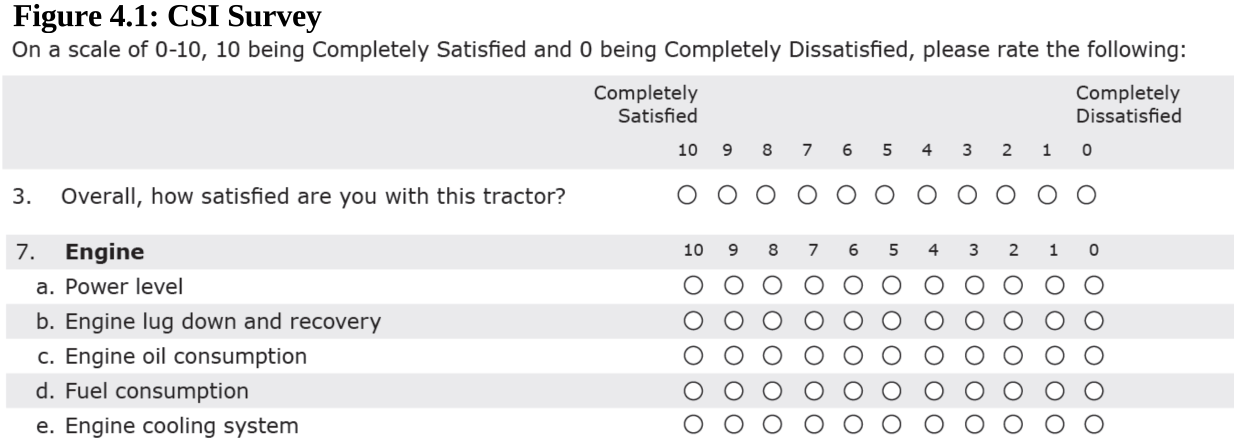
Regression analysis will also be used as a statistical technique that attempts to "explain" movements in one variable, the dependent variable, as a function of movements in a set of independent variables (Studenmund 2011). This procedure allows one to examine how changes in independent variables cause a change in the dependent variables. There are a couple of key statistics to look at that tell you if the analysis is significant or not. R-Squared estimates the sample predictive power. As R-squared is closer to one, the predictive power is higher. The t-statistic is another important measure, the larger in absolute value the t-value is, the greater the likelihood that the estimated regression coefficient is statistically different from zero (Studenmund 2011). A t-value with an absolute value of two or greater usually has a 95% probability or better that the estimated parameter value does not equal zero. Another important set of statistics to examine are the estimated coefficients. If these numbers are positive and statistically significant then they have a positive correlation with the dependent variable. If they are negative and statistically significant then they have a negative correlation with the dependent variable. The magnitude of the coefficient provides a quantitative estimate of the economic importance or the marginal impact on the dependent variable, customer satisfaction.

These statistical analyses will be conducted under two scenarios. The first scenario will be for the overall machine system. The second scenario will be on a specific subsystem, the engine subsystem, to understand the impact the analysis has on a specific subsystem in combination with the overall machine.

4.2 Data

Customer satisfaction data was collected using a ten point likert scale question from a customer satisfaction survey. Figure 4.1 shows the two questions and their sub points. Question three or the overall customer satisfaction question asks customers their overall satisfaction with the machine being examined. The next question being analyzed asks the customer to rank their satisfaction for the engine related subsystem. The analysis will average the engine subsystem rankings by each machine to get a combined engine sub system ranking. This was done by averaging the scores in the question. John Deere sends a survey out to every customer after six months from the date of delivery of their equipment. This allows customers to have a use season before they provide feedback. Customers who own multiple machines receive a survey for each machine. Average response rate of surveys are 28%. Data from the previous two years 2011-2012 is used in the analysis and overall CSI score and a composite for the engine subsystem will be the dependent variables in the analysis. This provided 520 data points for analysis. In the analysis, the customer satisfaction scores were scaled a factor of 10. As an example a customer score of 10 = 100 and a customer score of 5 = 50. Thus, scores could range from 0-100.

Figure 4.1: CSI Survey



On a scale of 0-10, 10 being Completely Satisfied and 0 being Completely Dissatisfied, please rate the following:

	Completely Satisfied 10	9	8	7	6	5	4	3	2	1	Completely Dissatisfied 0
3. Overall, how satisfied are you with this tractor?	○	○	○	○	○	○	○	○	○	○	○
7. **Engine**	10	9	8	7	6	5	4	3	2	1	0
a. Power level	○	○	○	○	○	○	○	○	○	○	○
b. Engine lug down and recovery	○	○	○	○	○	○	○	○	○	○	○
c. Engine oil consumption	○	○	○	○	○	○	○	○	○	○	○
d. Fuel consumption	○	○	○	○	○	○	○	○	○	○	○
e. Engine cooling system	○	○	○	○	○	○	○	○	○	○	○

Machine data for diagnostic trouble codes is gathered using cellular technology allowing machine data to be wirelessly transmitted on a daily basis. When a machine exhibits a diagnostic trouble code it sends the data in via cellular modem to a data base where the information is made available for customers and dealers. This technology has been standard on equipment since 2011. Data for the last two years on 8R row crop tractors was gathered for this analysis. Data from the two years contained over 45,000 DTC's. Table 4.1 shows an excerpt from the data set. Each machine product identification number (PIN) shows the quantity of three types of DTC's. Informational DTC's typically don't have a major impact on machine performance and are for operator awareness. Informational codes can include benign codes such as operator out of seat. Red DTC's are critical machine codes that are usually an indication to the operator that the machine requires immediate attention and should be stopped or shut-down, such as engine oil pressure is low. Yellow codes lie in the area in-between informational and red and may at times require the operator to do maintenance on the machine. An example would be hydraulic oil filter restricted. "Total" is the sum of all three of these code categories summed.

Table 4.1: Diagnostic Trouble Code Sample Data

Machine PIN	INFORMATIONAL	RED	YELLOW	Total
RW8235R040227			6	6
RW8235R041061	16		36	52
RW8235R041114	62		116	178
RW8235R041136			4	4
RW8235R041153	26		44	70
RW8235R041192	22		60	82
RW8235R041227	66	2	44	112

Note: Machine PIN is a unique machine identifier for each machine. Informational codes can include benign codes such as operator out of seat. Red DTC's are critical machine codes and require immediate attention such as engine oil pressure low. Yellow codes require the operator to do maintenance on the machine an example would be hydraulic oil filter restricted. Total is the sum of all three of these code categories.

Data was selected using the following criteria. Each unique machine product identification number (PIN) had to have CSI survey returned for the machine PIN and there needed to be data on machines' DTCs. The limiting factor in machine DTC observations was that data only began being collected in 2011. This provided approximately two years worth of machine DTC data for this analysis.

Next machine DTC data was then limited to a time frame of eight months from date of manufacture. Limiting machine DTC data to eight months from date of manufacture aligns with the time the machine was in use with the customer to the time they filled out the CSI survey. Because surveys are sent out no sooner than six months after the date of delivery and on average there is a transit time between date of manufacture and delivery, which is estimated to be two months on average. A total of 636 machines were available based on these criteria. Data was then cleaned by removing entries with blank data points. Blank data points were the result of customer not completing that specific question on the survey. This reduced data points down to 520 available machines.

4.3 Statistical Methods

Statistical analysis includes summary statistics providing a summary of the data being analyzed. It provides the mean, standard deviation, minimum, maximum, number of diagnostic trouble codes exhibited by each machine and total count of machines in the data set.

Analysis using a histogram will be conducted to provide an understanding of how many machines exhibit specified quantity of DTC's. This will provide an idea of how many machines generate a large number of DTC's versus how many machines generate very few DTC's.

A correlation analysis will be conducted on the overall CSI score and each type of DTC, this includes informational, yellow, red, as well as the total DTC's. It is anticipated these will have a negative correlation, meaning as the number of DTC's increase the CSI score will decrease. This is assumed for both CSI scores being examined.

Regression analysis will be estimated on the overall machine and on the engine subsystem. The overall machine will have the independent variable being all DTC's generated by each machine. This is to understand the impact all DTC's have on the overall satisfaction. The linear regression equation will be as follows: Y= f(x) + e, where Y is Overall CSI; X is the quantity of each type of DTC's and/or the grand total; e is mean zero, independent and normally distributed random error term; and f is assumed to be a linear function. The expected sign of the coefficients on each DTC variable is for them to be negative. That is, as the quantity of DTC's increase, the overall CSI will decrease.

The regression analysis of the engine subsystem will have a dependent variable of the average engine CSI and independent variable being, all engine DTC's. Only DTC's that are specific to the engine subsystem will be filtered out and included in this analysis. The linear regression equation will be as follows: Y= f(x) + e, where Y is the composite CSI of the engine subsystem; X is the quantity of DTC's for the engine subsystem; e is mean zero, independent and normally distributed random error term; and f is assumed to be a linear function. I expect a negative sign on the DTC variable coefficient. That is, as the number of DTC's increases there will be a decrease in customer satisfaction for the engine subsystem. Analysis on the engine subsystem will be conducted to understand the impact a specific subsystem may have on that subsystem satisfaction.

CHAPTER V: RESULTS AND DISCUSSION

This chapter will discuss the results of statistical analysis and impact DTC's have on customer satisfaction for the overall machine and the engine subsystem. This will also discuss some of the shortcomings with the current satisfaction survey.

5.1 Summary Statistics

Initial statistical analysis was conducted on the data to gain an understanding of the data set. Table 5.1.1 shows the summary statistics for the overall machine variables included in the statistical analysis. The column titled "informational" shows the mean, standard deviation, minimum, maximum, and count of informational codes for 520 machines used in the analysis. Informational codes exhibited by the machine are of the lowest priority. The column titled "yellow" shows the summary statistics for yellow codes which are the next level of priority. The column titled "red" shows the summary statistics for red codes which are the highest priority. The column titled "total" is the summary statistics for the sum of all three levels of codes. "Overall CSI" score in the last column shows the stats on CSI or customer satisfaction index from the survey for question that asked for the overall satisfaction.

The summary statistics indicate that yellow DTC's generate the most DTC's on average indicated by the mean of 35. Standard deviation is fairly large for informational, red, and total DTC's indicating the data points are not clustered around the mean. Overall CSI has a mean of 89 out of a maximum of a 100 indicating that a majority of the CSI scores are fairly high scores. In addition, it should be noted again that the CSI score has scaled by a factor of 10 from the survey likert scale of 1 to10. The total count of machines is 520 and of those 520 machines: 468 experienced yellow codes; 401 experienced informational codes; and 53 experienced red codes. The lowest numbers of machines were those experiencing red codes and they have the lowest maximum number of DTC's with a maximum value of 28.

Table 5.1.1: Summary Statistics Overall Machine

	INFORMATIONAL	YELLOW	RED	Total	Overall CSI
Mean	27	35	4	53	89
Standard Deviation	35	5	46	70	18
Minimum	2	2	2	2	0
Maximum	230	328	28	464	100
Count	401	468	53	520	520

Table 5.1.2 shows the summary statistics for the engine subsystem (ECU) variables included in the statistical analysis. The column titled "informational" shows the mean, standard deviation, minimum, maximum, and count of informational codes for 510 machines used in the analysis. Data points were limited to 510 due to engine satisfaction questions not being answered by customer providing incomplete data points. Informational codes exhibited by the machine are of the lowest priority. The column titled "yellow" shows the summary statistics for yellow codes which are the next level of priority. The column titled "red" shows the summary statistics for red codes which are the highest priority. The column titled "ECU" total is the summary statistics for the sum of all three levels of codes. "ECU CSI" scores in the last column shows the stats on CSI or customer satisfaction index from the survey for question that asked for the overall satisfaction of the engine subsystem. The summary statistics for the engine subsystem indicates there are only 510 machines total. Of those machines only 21 of them experienced a red DTC and 266 of the 510 machines experienced a yellow DTC and 103 machines experienced an

informational DTC. The mean for these DTC's are all rather low with yellow having the highest with 5. The CSI is slighter higher for the engine subsystem with a value of 92 compared to an overall CSI mean of 89.

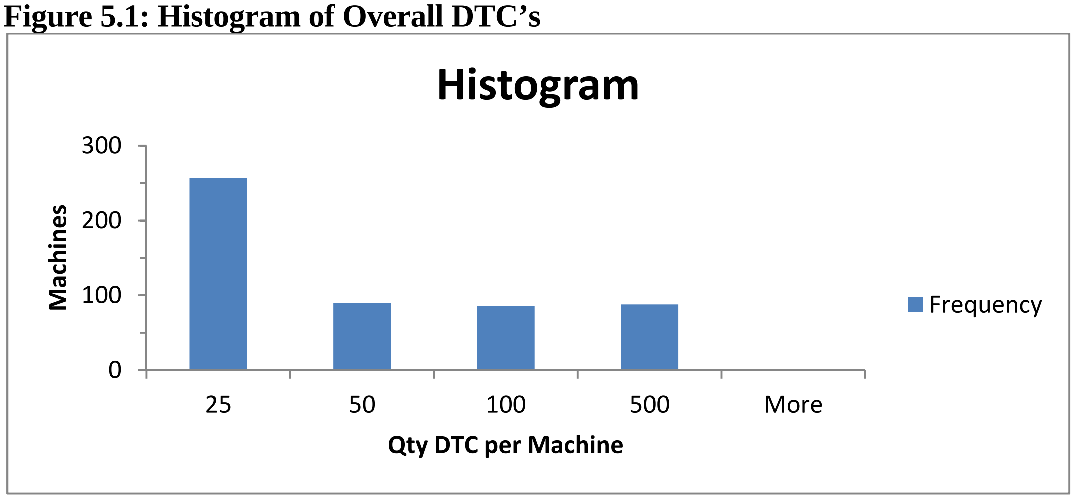
Table 5.1.2: Summary Statistics Engine Subsystem

	ECU INFORMATIONAL	ECU YELLOW	ECU RED	ECU Total	ECU CSI
Mean	1	5	0	7	92
Standard Deviation	4	14	1	16	11
Minimum	0	0	0	0	20
Maximum	34	176	12	182	100
Count	103	266	21	282	510

5.2 Histogram

To better understand the frequency of DTC's generated by a machine, a histogram was used to analyze the data. The histogram indicates that nearly 50% of the machines experience 25 DTC's or fewer. Only 88 of the 520 machines experienced over 100 DTC's. Using a histogram provides a better idea of the distribution of DTC's across individual machines.

Figure 5.1: Histogram of Overall DTC's



5.3 Correlation Analysis

Correlation analysis was completed to confirm the hypothesized negative correlation and understand the magnitude of these findings. Correlation analysis found a negative relationship between CSI and DTC codes, indicating that overall CSI score will decrease as alerts increase. Table 5.3.1 shows the correlation analysis results. As noted previously, a correlation of zero indicates the data series are unrelated and a value of -1 indicates the series would move in the exact opposite direction. The factor of -0.15 for the "total of all DTCs" ("Total") was statistically different from zero and indicates there is a small negative correlation between this factor and overall CSI. This finding aligns with the hypothesis that an increase in diagnostic codes exhibited by a customer's tractor will indeed decrease their satisfaction with the product.

Table 5.3.1: Correlation Analysis Overall Machine

	INFORMATIONAL	YELLOW	RED	Total
Overall CSI	-0.12	-0.11	-0.06	-0.15
P-Value	0.0015	0.0062	0.0155	0.0008

P-Values are all significant at the 5% level.

Table 5.3.2 shows the correlation analysis for the engine subsystem. This analysis is interesting in that it shows a very small positive correlation for informational and yellow DTC's, however it shows a stronger negative correlation for red DTC's, which was the only one significantly different from zero. The positive correlations are somewhat counter-intuitive to what would be expected, but they are very small at 0.03 and are not significantly different from zero. The ECU total shows a very small negative correlation basically at zero, indicating ECU codes have a negligible impact on engine subsystem CSI.

Table 5.3.2: Correlation Analysis Engine Sub System

	ECU INFORMATIONAL	ECU YELLOW	ECU RED	ECU Total
Engine CSI	0.03	0.03	-0.34	-0.00019
P-Value	0.1663	0.6615	0.0157	0.9028

P-Values indicate only ECU RED significant at the 5% level.

Table 5.3.3 shows the relationship of CSI score to the average number of DTC occurrences. The first three columns show that as CSI decreases the average number of DTC's continue to increase in all DTC categories. This occurs up until the last column of a CSI score of 49-0 where the average number of DTC's decreased, yet satisfaction significantly decreased. While the first three columns support the argument as DTC's increase the satisfaction decreases, the final column indicates there are still other factors that may cause a decrease in satisfaction.

Table 5.3.3: CSI vs. Average DTC's

		CSI Score			
		100-90	**89-70**	**69-50**	**49-0**
Ave. DTC's	**Informational**	16	26	41	31
	Yellow	26	32	45	47
	Red	0	1	3	1
	Total	43	59	89	79

5.4 Regression Analysis

Table 5.4.1 shows the linear regression estimation results with the dependent variable of overall CSI and the independent variable of total of DTCs. This regression model is predicting CSI as a function of the total number of DTC's. This model has an R-squared value of 0.02. An R-squared value closer to 1 would indicate the regression is a more accurate predictor. The low R-squared value of 0.02 indicates there is a lot of un-modeled information. Both the t- stats and P-values indicate the independent variable is significant at a 95% level of confidence. The coefficient on “total” indicates that for every DTC that is generated by a machine the CSI score will decrease by 0.04. This means for every 100 DTC’s a machine generates one could expect to see a 4 point decrease in customer satisfaction out of 100 points. Due to low R square value this could be somewhat inconclusive, as very little of the data variability is being modeled. In addition, regression does not indicate causation, meaning there may be other factors in addition to DTC’s that may be resulting in customer dissatisfaction.

Table 5.4.1: CSI Regression Model Overall Machine

R Square	0.02			
Standard Error	17.70			
Observations	520			
	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	91.21	0.96	95.29	0.000000
Total	-0.04	0.01	-3.39	0.000761

Given the values of the regression in table 5.4.1, another regression was estimated examining the impact of the separate DTC types being included as covariates. Estimation results are shown in table 5.4.2. Again, the R-square value is still very low, indicating the model doesn’t do a very good job of explaining the data. In addition to the low R square value, the t-stats for each of the independent variables indicate that none of the marginal impacts of these codes individually are statistically different from zero. The “total” provides a different measure, indicating that customers may be more impacted by the number of codes, rather than the type of code.

Table 5.4.2: CSI Regression Model Overall Machine Individual

R Square	0.03			
Adj R Square	0.02			
Standard Error	17.74			
Observations	521			
	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	91.33	0.98	93.65	0.000000
INFORMATIONAL	-0.05	0.03	-1.75	0.079965
RED	-0.61	0.38	-1.60	0.110613
YELLOW	-0.02	0.02	-0.96	0.337684

5.5 Engine Sub System Analysis

An additional regression analysis was run on data specific to the engine subsystem. This was done to see the impact a major subsystem of an 8R row crop tractor had on customer satisfaction. The dependent variable is the average engine CSI and the independent variable was total Engine Controller Unit (ECU) DTC codes. ECU codes are specific to the engine subsystem and directly impact performance of the engine sub system. The estimation results in Table 5.5 indicate the model was not very good at explaining the variability in the data, as evidenced by the very low R-square. The t-Stat of 0.0031 indicates a strong probability that the marginal effects from ECU codes are not statistically different from zero.

A regression was completed on ECU codes by type: Informational, Red, and Yellow to see if a customer would be impacted by the type of code vs. the number of codes in the engine sub system. The findings were similar to that of Table 5.4.2 where the R square value was low (.03) and the t-stat for informational codes and yellow codes were below 2 indicating they are not statistically different from zero. The red code type was significant with a t-stat of 2.38 and a coefficient of -1.01, indicating that red engine DTC's have a significant effect on average engine CSI. For every red ECU alert we could possibly see a 1.01 point reduction in average engine CSI score on a 100 point scale.

Table 5.5: Engine Subsystem Regression Model

R Square	0.00000004			
Standard Error	10.83266105			
Observations	510			
	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	91.5177855	0.7554	121.152	6E-244
ECU Total	-0.000101704	0.03232	-0.0031	0.99749

5.6 Customer Satisfaction Survey Discussion

The current customer satisfaction survey (CSI) provides adequate customer feedback on overall customer satisfaction of the machine. The CSI survey is focused on attributes of the machine the customer interacts with such as cab features, ride quality, performance. The specific question that asks about overall satisfaction was used in the analysis to determine the impact DTC's have on CSI. The CSI survey does provide adequate CSI feedback on the engine subsystem to carry out analysis on that subsystem. However, it does not do an adequate job aligning each of the major electronic controllers with a question on the survey. This prevented analysis to be done on other subsystems such as the transmission. Without this, it is difficult or impossible to analyze the other individual subsystems of the machine. The CSI survey also does not identify key customer demographics such as size of operation, age of owner, or dealer, which could provide additional data to better explain the variability and impact DTC's have on customer satisfaction. There needs to be additional consideration on how the survey could be restructured to accommodate future analysis using DTC data.

Analysis does indicate that DTC’s may have an effect on customer satisfaction. For this reason, a question(s) should be considered on the survey specifically related to DTCs and DTC’s related to individual subsystems, such as the engine and transmission.

CHAPTER VI: CONCLUSIONS

The purpose of this research is to examine the usefulness of using primary diagnostic data collected by John Deere to assess customer satisfaction. Specifically, to examine if the quantity of diagnostic trouble codes (DTCs) a John Deere 8R series row crop tractor experiences has an impact on customer satisfaction scores reported on surveys. Specific objectives of this research were to: (i) Evaluate the impact machine diagnostic trouble codes have on customer satisfaction; (ii)Evaluate the current customer feedback system to identify its strengths and weaknesses; (iii)Identify a proactive approach that targets customers that may have a reduced satisfaction score due to the number of DTC's generated by a machine.

Linear regression analysis was used to assess whether a model can be found that explains the relationship between customer satisfaction index (CSI) and the number of diagnostic trouble codes (DTC's) exhibited by an 8R series row crop tractor. The analysis indicated there is a negative correlation between the CSI score and the number of DTC occurrences when looking at the overall machine. This makes logical sense as a DTC would indicate a potential issue or failure point for the machine, potentially having a negative effect on machine performance and customer satisfaction. The engine subsystem correlation analysis found the correlation for red codes to be negative as hypothesized, yet the most of the other correlations and DTC variables were not significantly different from zero.

Examinations using regression on the overall machine analysis indicate that for every 100 Total DTC's a machine exhibits one could expect to see a 4 point reduction in overall CSI score by the customer. Keeping in mind the model did have a low R squared value, indicating the model did not explain a significant amount of variability. In addition, regression does not indicate causation, meaning there may be other factors in addition to DTC's that are causing customer dissatisfaction. This information may prove valuable in being able to understand customer satisfaction more proactively, but needs to be empirically examined and better understood with further examination. John Deere is able to monitor the number of DTC's a machine generates on a daily basis and can proactively identify machines that generate enough DTC's that would have an impact on customer satisfaction, helping to possibly implement a process for dealers and field teams to proactively assess the needs of the customer in a effort to mitigate customer dissatisfaction. This proactive approach would monitor machine DTC's on a daily basis and flag machines that have generated a specified number of codes. The identified machines can then be communicated to the responsible dealer allowing the dealer to proactively work with the end customer to resolve the issues with the machine and prevent customer dissatisfaction. This will enhance the customer experience, satisfaction and ultimately result in higher customer retention, securing future sales for the dealer channel and John Deere.

Future considerations for additional analysis would include the ability to determine the specific date of delivery and time frame the customer used the machine before they filled out the survey to precisely align with the data. Including other variables in the model could also prove to be advantageous. Restructuring of the CSI survey sent to customers will be required to provide additional data points that could help to explain overall variability in CSI. CSI survey data points to be considered for addition into the survey included customer demographic factors such as age and size of operation, which could help to improve model estimates and do a better job of explaining the variability in customer satisfaction data. Having variables such as regional location information or selling dealer could also help. The selling dealer could have an impact on overall customer satisfaction based on the level of support they currently provide to their customer. Having a question that provides customers perception of dealer performance would help to understand if the dealer is providing adequate level of service. Regional demographic information could help to explain if customers from different cropping regions are more critical of their machine performance and expectations. Future research would also include looking at the occurrence of the DTC, specifically the time stamp when the DTC occurred, to determine if the time of year has an impact. For example, spring planting DTC’s are more critical than DTC’s that occur during fall tillage on 8R tractors. Additional research should also include identifying correlation by individual tractor models. Finally doing further analysis on additional platforms such as harvesting equipment or spraying equipment would help to understand if there are consistencies across platforms and the model is consistent.

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