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An Empirical Study to Develop a Decision Support System (DSS) for Measuring the Impact of Quality Measurements over Agile Software Development (ASD)

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Abstract

Background/Objectives: Primarily, this quantitative research aims to study the impact of integrating quality measurements with ASD, quantify it, and develop a DSS for predicting its outcome. **Methods/Statistical Analysis:** Included within a survey, the population sample is represented by project managers, who were divided into two independent groups: The first one adopts an explicit quality measurement framework while the second group does not apply quality measurements. After that, the researcher tested both groups in an independent samples t-test, and analysed results statistically. After experimenting different machine learning models, the researcher developed a DSS based on Linear Regression. **Findings**: Only 150 responded out of 200 respondents. The research dataset passed the "independent t-test" validity test with the fulfilment of the six assumptions. After conducting the independent t-test design, the researcher found that the value of Sig. (2-tailed) is less than .05, which means that the differences between the experimented groups are statistically significant. After that, the researcher utilized WEKA experimenter with 10-folds cross validation to test the dataset fitness with four different machine learning algorithms, which are Linear Regression (base), Multilayer Perceptron, KStar, and Decision Stump. The results showed that Linear Regression (base) provides better fitness with the dataset. Moreover, The R Square for it is .836. Based on Linear Regression, the researcher developed web and windows version of the DSS using VB.NET. In summary, research results shows that there is empirical evidence to support the proposition that quality measurements integration with ASD presents a strategic value to organizations. The contribution of these findings is materialized in its empirical nature and the scariness of research in this domain. **Application/Improvements:** Henceforward, the researcher are planning to expand the population sample, publishing the developed DSS online with integrated feedback, and developing other DSSs for supporting integrating quality measurements with ASD.

Keywords: Agile Software Development (ASD), Decision Support System (DSS), Independent T-Test Design, Linear Regression, Quality Measurements, Strategic Alignment (SA), Strategic Information Systems (SIS)

1. Introduction

1.1 Overview

ASD has emerged as one of the most successful trends in software engineering[1–5]. Indeed, the literature review reveals a considerable amount of evidence to support this view. Similarly, the literature review shows the strategic importance of integrating quality measurements within software engineering methodologies. However, as the literature review indicates, there is a lack of research on the strategic impact of quality measurements over ASD. Arguably, introducing quality measurements into ASD must improve ASD processes. Consequently, IT manag-

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ers must incorporate quality measurements within ASD processes. However, with the emergence of SA and SIS, IT decision making has become one of strategic management concerns[6,7]. Certainly, IT managers are not dictating IT decision making any more. In fact, IT managers must demonstrate the strategic value of their decisions to top managers, who dominate financial decisions or decisions with financial sequences[8]. Accordingly, IT managers must consult the top managers before proceeding with these decisions. In this context, applying quality measurements with ASD implies financial and organizational implications[9]. Consequently, top managers need to appreciate the strategic implications of integrating quality measurements within ASD. However, in accordance with the literature review, there are clear gaps in this research area. Motivated by the scariness of research in this area[10], the research attempts to contribute to research efforts in narrowing the gaps in this research area and providing empirical evidence for approving the positive relation between quality measurements and ASD. Moreover, the research attempts to develop a dedicated DSS to quantify and predict the outcome of this relation. The next section lists research questions.

1.2 Research Questions

Based on the problem description, the research developed the following questions:

1. What is the impact of integrating quality measurements with ASD?
2. In empirical sense, is there a strategic value for integrating quality measurements with ASD?
3. Is there a possibility to develop a decision support system for helping managers in measuring the value of integrating quality measurements with ASD?

1.3 Research Objectives

Based on the problem description and research questions, the research developed the following objectives:

1. To research, and critically evaluate the relation between quality measurements and ASD.
2. To research, and critically evaluate the strategic value of integrating quality measurements with ASD.
3. To develop a decision support system for measuring the strategic value of integrating quality measurements with ASD.

1.4 Literature Review

IT Business environment is a field for fierce competition[11,12]. Therefore, business organizations employ their abilities in order to compete and achieve the competitive advantage[13,14]. Moreover, customers play a fundamental role in the outcome of these competitions[12,15]. Accordingly, organisations are competing to develop services for satisfying their customers. Under such circumstances, organizations rushed to develop reliable quality assessment systems[16]. The next section introduces ASD and its main values. After that, the research reviews previous research on software measurements. The literature review may enable the research to respond to research questions one and two, and research objectives one and two.

1.4.1 ASD and Its Main Values

ASD have emerged as a modernized methodology for developing software applications[17,18]. Indeed, ASD methods have been successfully implemented in many IT organisations, and the principles of ASD influenced wide range of software development methodologies[19–23].

The agile methodologies contain pragmatic solutions to software problems that focus on leveraging software development mechanisms and making stakeholders the most important[17,24]. According to the agile manifesto[17], the following are the four main values of ASD.

1.4.1.1 Individuals and Interactions over Processes and Tools

ASD starts with understanding stakeholders and their capabilities, requirements, and interactions. After that, ASD determines what level of resources and tools is required for a given project[5,25].

1.4.1.2 Working Software and Comprehensive Documentation

ASD methodology tends to document the least possible amount of project data. Naturally, large ASD projects require much more documentation and trace matrices than small projects[26].

1.4.1.3 Customer Collaboration and Contract Negotiation

ASD undermines the role of contracts in software projects. Without contracts, the iterative delivery approach can work in a flexible manner and lead to developing a competitive product with strategic implications[27].

1.4.1.4 Responding to Change over following a Plan

Instead of using detailed and fixed schedules, ASD process replaces project plans with flexible charts, which can accommodate with immediate developments and track project progress effectively[28].

1.5 Previous Research on Software Measurements

There is a tendency amongst researchers to highlight the importance of quality measurements over software engineering models, such as ASD and waterfall model[29–32]. Indeed, researchers use metrics every day to understand, control and improve software development processes. Large IT companies, such as HP, Microsoft, IBM, and Oracle, widely use metrics in their operations[33].

Researchers suggest the following as motivations for using quality measurements in ASD[31,34]:

- Improve Project planning, control, and estimation.
- Improve Project management, control, and tracking.
- Improve quality management and align project objectives with business objectives.

Researchers conducted several studies[35–38] on object-oriented product metrics. Bellini[39] explained the evolution of software measurements, besides the impact of measurements over software engineering. However, researchers need to conduct more research on aligning research for metrics with business requirements, especially in large industrial context[40,41].

Kupiainen, Mantyla, and Itkonen[10] concede, despite of the importance of measurements, within organizational context, empirical metric research in the area of ASD remains scarce. In brief, neither of the previously mentioned studies focused on studying the strategic impact of integrating quality measurements with ASD nor they focused on providing empirical evidence for supporting it. Motivated by research questions and objectives, the research attempts to narrow this research gap through conducting an experimental study. Accordingly, the next section explains research methodology.

2. Methodology

To begin with, section 2.1 explains the conceptual frame work for the research. After that, section 2.2 explains the experiment and survey design. Finally yet importantly, section 2.3 explains the statistical design.

2.1 Conceptual Framework

As Figure 1 show, the conceptual framework is divided into five sections; the following is a brief description of them:

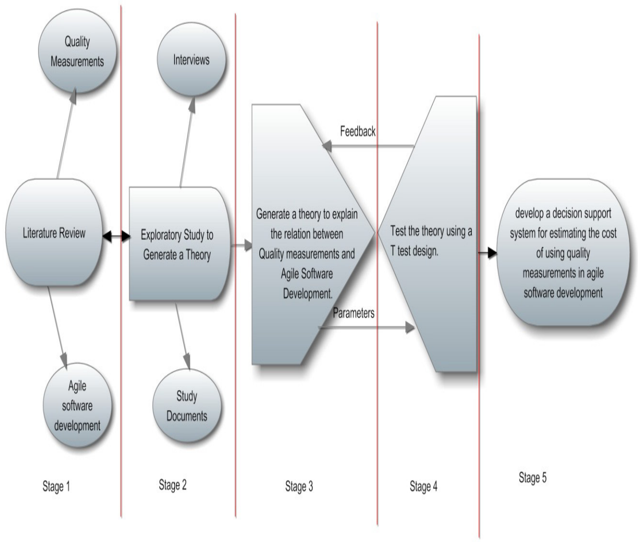

Figure 1. The conceptual framework for the research.

2.1.1 Stage 1: Literature Review

This stage aims to provide a critical review to quality measurements area and its relation with ASD.

2.1.2 Stage 2: An Exploratory Study to Generate a Theory for Explaining the Relation between Quality Measurements and ASD

The researcher conducted face to-face interviews and examined written artefacts of the institution.

2.1.3 Stage 3: Generate a Basic Theory to Explain the Relation between Quality Measurements and ASD

The researcher generated a basic theory based on the analysis of the data taken from the previous stage.

2.1.4 Stage 4: Test the Basic Theory using a Quantitative Method

After conducting a survey to collect the data, the researcher chooses independent t-test statistical design[42,43] to explain the dataset and its associations.

2.1.5 Stage 5, Develop a DSS

After examining the independent t test results and comparing four machine learning algorithms, the research selected linear regression to develop a DSS for estimating the cost of ASD based on lead time and quality measurements application. The next section discusses the experiment and survey design.

2.2 Experiment and Survey Design

As explained in research questions and research objectives, the research faces two challenges; firstly, the research must find the strategic implications of integrating quality measurements with ASD; secondly, if this relation exists, the researcher must quantify it using reliable measurements. In this context, business strategies aim to find a way of achieving the competitive advantage against competitors in the market[44–46]. Michael Porter identified two strategies to achieve the competitive advantage, cost leadership strategy and differentiation strategy[47,48]. In this research context, the research adopts cost leadership approach to define strategy because it assumes that the relation between quality measurements and cost leadership strategy can be identified and quantified empirically. Indeed, in cost leadership context, the strategic value for integrating quality measurements with ASD can be measured using ASD cost as a dependent variable.

In order to measure experiment variables, the research conducted a survey to collect information about ASD project cost and development time. To reduce the interference of confounding variables, the survey contained a proposal for an ASD project. Indeed, the project proposal is entitled "Traffic Monitoring System", which was developed by a group of students at Rutgers University[49]. Along with the project source code, the project documentation contains a wealth of information about the project and its details. Indeed, these details include user requirements, effort estimation, functional requirements, domain analysis, class diagrams, system architecture, system design, and much more details[49]. As explained in section "3.1. Pilot study", the participants were instructed to evaluate the project and answer two questions, which are: 1. What is the overall cost of developing the ASD project? 2. What is the lead time for developing the ASD project? The project requirements reflect the experiment variables, which are identified in Figure 2. Furthermore, the researcher grouped respondents into two groups: firstly, group "Yes", which represents respondents who apply quality measurements; secondly, group "No", which represents respondents who didn't apply quality measurements. The respondents must determine the project cost and lead time based on the project proposal. Lead time refers to the time elapsed between a customer requesting for a solution and receiving the final solution. Similarly, Overall cost refers to project development costs during the same period.

Finally yet most importantly, the research examines the difference between the two groups in order to answer the research questions. Figure 2. represents the experiment variables. These variables are categorized as follow:

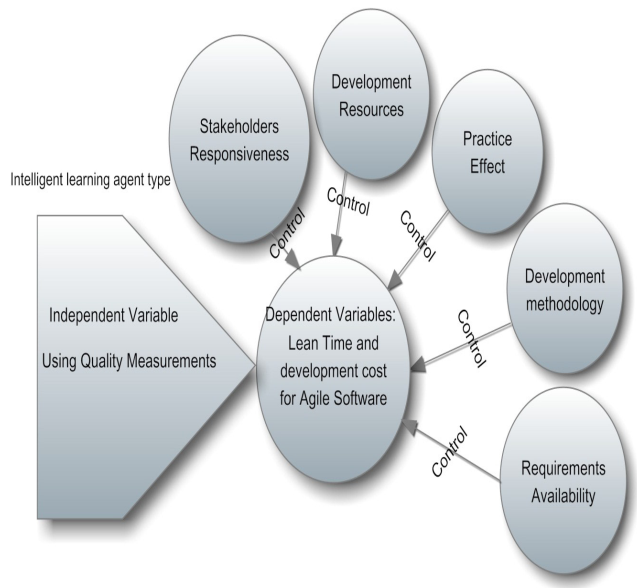

Figure 2. Experiment variables.

2.2.1 Independent Variables

Quality measurement is the independent variable. Indeed, the first group, entitled "Yes", adopts an explicit quality measurement framework while the second group, entitled "No", does not apply quality measurements.

2.2.2 Dependent Variables

As discussed earlier in section "2.2-experiment and survey design", lead time and development costs are the dependent variables. The test measures lead time in hours and development costs in dollars.

2.2.3 Control Variables

The experiment design aims to control the values of these variables. In fact, the project proposal presented these variables in detailed manner[49]. To illustrate, these variables are as follow:

2.2.3.1 Stakeholders Responsiveness

This variable presents stakeholders response to ASD project inquiries, whether these stakeholders are users, clients, or employees. The project proposal categorized stakeholders and detailed their role in the project.

2.2.3.2 Development Resources

These resources present availability, number of team members, software tools, and so forth. The project proposal determined the values of these variables explicitly.

2.2.3.3 Practice Effect

This variable presents influences on experiment that arises from experience with similar projects. The project proposal presented information about the nature of participants.

2.2.3.4 Development Methodology

The project proposal assumes using Agile Scrum Methodology. Scrum is a flexible agile project management framework for managing agile projects through iterative and incremental stages[50,51]. The next section presents the statistical design.

2.3 Statistical Design

The research divided this section into two sections, the first section defines research hypothesis while the second section examines the dataset validity for independent t-test.

2.3.1 Hypothesis

The null hypothesis for the independent t-test[42] suggests that the population means from the unrelated groups "Yes and "No" are equal. The following is the null hypothesis:

H_0: $\mu_{cost1} = \mu_{cost2}$ and $\mu_{leadtime1} = \mu_{leadtime2}$

In this research context, the researcher is testing to see if he can reject the null hypothesis and accept the alternative hypothesis, which suggests that the population means are not equal. On the other hand, the following is the alternate hypothesis:

H_1: $(\mu_{cost1} \neq \mu_{cost2}$ and $\mu_{leadtime1} = \mu_{leadtime2})$ or $(\mu_{cost1} = \mu_{cost2}$ and $\mu_{leadtime1} \neq \mu_{leadtime2})$ or $(\mu_{cost1} \neq \mu_{cost2}$ and $\mu_{leadtime1} \neq \mu_{leadtime2})$.

If H0 is true then using quality measurements has no effects on both lead-time and cost of ASD. Hence, it has no strategic importance for ASD. However, if H0 is false then this provides support for the inference that using quality measurements has effects over lead time and cost of ASD. Consequently, the researcher can infer that there is evidence to support the proposition that quality measurements integration with ASD presents a strategic value to business organizations. The next section examines the validity of the dataset for independent t-test.

2.3.2 Independent t-Test Validity

This section tests whether the dataset can be analysed using an independent t-test[42] or not. Indeed, the dataset must pass six assumptions that are essential to validate the results of the independent t-test. The following points test the dataset against these assumptions:

- Dependent variable must be measured using a continuous scale: The dependent variables are continuous variables.
- Independent variable levels must be categorized into two independent groups: As discussed in section 2.2, experiment and survey design, the quality measurement variable is an independent variable that is divided into two groups.
- Independence of observations: Each participant is a member of one group.
- There should be no significant outliers: outliers are data points that present deviations to the usual pattern. Figure 3 presents box plot for the independent and dependent variables. Looking at Figure 3 (a), cases 47, 49 present outliers in group "Yes" while cases 21, 132 present outliers in group "No". The test requires removing these outliers because they may have negative effect on the validity of the results[52]. On the other hand, Figure 3 (b) shows no outliers, which eliminates the need for additional modifications.
- Dependent variable must be approximately normally distributed: After removing the cases identified in the previous section, the researcher conducted a normality test to the dataset. As Table 1 shows, both tests Kolmogorov-Smirnov[53] and Shapiro-Wilk[53] show that p value is above .05

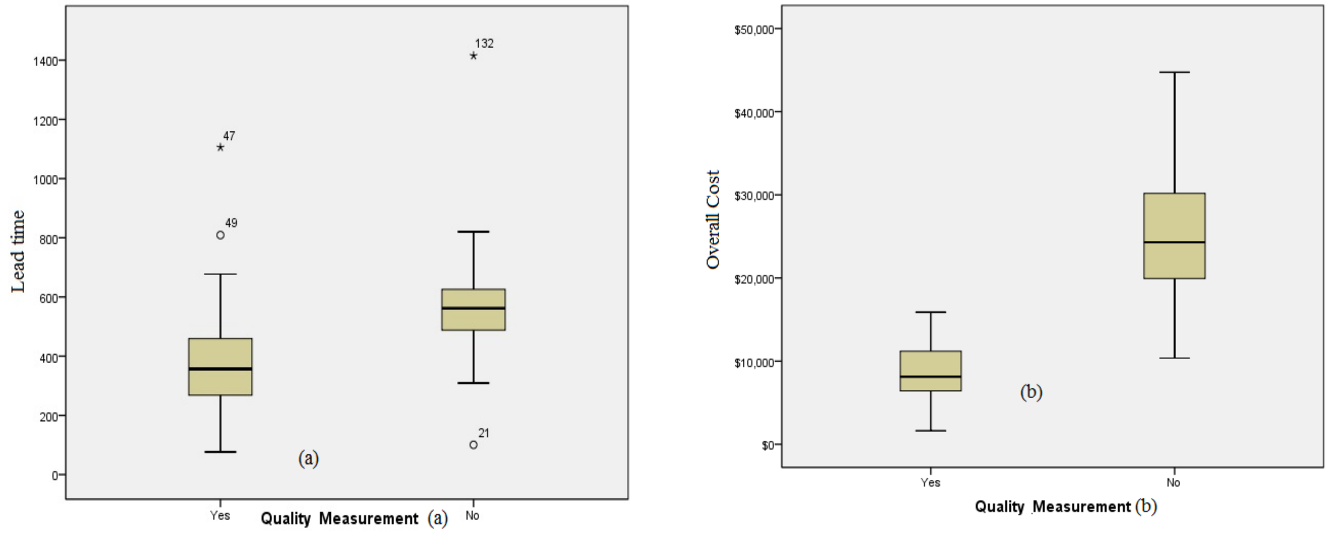

Figure 3. Boxplots, (a) Boxplot for variable "lead time". (b) Boxplot for variable "Overall cost".

Table 1. Tests of Normality

	Applying Quality Measurement	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
		Statistic	df	Sig.	Statistic	df	Sig.
Overall Cost	Yes	.088	79	.200*	.976	79	.148
	No	.100	71	.077	.973	71	.132
Lead Time	Yes	.067	79	.200*	.992	79	.912
	No	.074	71	.200*	.992	71	.935

a. Lilliefors Significance Correction.
*This is represents a lower bound of the true significance.

Table 2. Correlation measurements for variables Overall Cost and Lead Time

	Applying Quality Measurement		Statistic	Std. Error
Overall Cost	Yes	Mean	$8,692.41	$379.616
		Skewness	.277	.271
		Kurtosis	-.628-	.535
	No	Mean	$25,032.95	$863.826
		Skewness	.430	.285
		Kurtosis	-.232-	.563
Lead Time	Yes	Mean	355.96	14.267
		Skewness	.107	.271
		Kurtosis	-.289-	.535
	No	Mean	562.15	12.183
		Skewness	-.018-	.285
		Kurtosis	-.161-	.563

Table 3. Levene's Test for variables Overall Cost and Lead Time

		Levene's Test for Equality of Variances	
		F	Sig.
Overall Cost	Equal variances assumed	40.966	.000
	Equal variances not assumed		
Lead Time	Equal variances assumed	2.791	.097
	Equal variances not assumed		

for all groups. Consequently, the results led us to accept the null hypothesis and conclude that the data is normally distributed[54].

In addition, Table 2 shows that Skewness and Kurtosis values[55] for all groups are close to zero. Hence, the researcher concludes that the data is normally distributed.

- Homogeneity of variances.

Looking at Table 3, Levene's Test[56], p value for Lead Time group is .097, which is greater than .05; this result leads us not to accept the null hypothesis, which means that the variability in both groups is not significantly different. On the other hand, p value for Overall Cost group is approximately .000, which is less than .05; this result leads us to accept the null hypothesis, which means that the variability in both groups is significantly different and corrections should be made prior to the independent t-test. In fact, these corrections will be explained in section 3.5, independent t-test results.

In conclusion, the dataset passed the six assumptions. Hence, it can be analysed using independent t-test and the results are expected to be reliable. The next section discusses the research results.

3. Results and Analysis

This section discusses the research results. To begin with, the research discusses pilot study results. After that, briefly, the research analyzes population sample and survey implementation briefly. Furthermore, the research analyses extreme points in the dataset. After that, the research discusses independent t-test, followed by validating the independent t-test results statistically. Finally yet importantly, the research develops a regression model for defining the relation between experiment variables.

3.1 Pilot Study

At first, the researcher conducted a pilot study to 10 respondents; five of them are system analysts and the rest are project managers. The pilot study showed that only project managers can provide a reliable analysis to the project proposal due to their experience in ASD projects management. As a response to pilot study results, the research targets only project managers. Additionally, the pilot study results showed that each manager calculates lead time and overall cost differently. Hence, it is difficult to calculate them through certain frame or template, which is formed of multiple questions. As discussed in section "2.2. Experiment and survey design", the survey questions were reduced from ten questions to two questions in order to reflect feedback from the pilot study.

3.2 Population Sample

Located in Asia, Jordan is a developing country with limited natural resources[57,58]. The Jordanian government utilizes Information Technology (IT) sector to contribute to the national income[59,60]. As discussed in "section 3.1. pilot study", the target population for this study is IT organizations in Jordan. The list of IT companies was derived from statistics provided by the Jordanian Ministry of Telecommunication and Information Technology, and the Jordanian Department of Statistics. According to the generated list, the number of companies operating in the sector is 1,537 company; moreover, operate sectors are telecommunications, technology, solutions for banking, electronic applications of the Internet, e-commerce solutions, government solutions, and branches of major international companies, such as Microsoft, Oracle, Cisco, STS, Orange, Zain, and so forth. The researcher used SPSS 20 to generate a random sample of 200 IT companies out of 1,537 IT companies using Simple Random Sampling (SRS)[61]. Project managers from each company were identified through their company's official website and through its page on Facebook.

3.3 Survey Implementation to Collect Data

The researcher sent 200 project proposals to all the respondents accompanied with the ASD project link[49] and a consent to act as a research subject (supplemented in Appendix A). Electronic survey software was used to send data for this study. Project Managers who decided to participate in the research, clicked on the ASD project link sent with e-mail. Of course, the consent form includes a note to confirm the anonymity of participants. As Table 4 indicates, only 154 emails were returned with full response (four cases were excluded because they represent out layers).

Table 4. Case Processing Summary

Applying Quality Measurements		Cases					
		Valid		Missing		Total	
		N	Percent	N	Percent	N	Percent
Lead_Time	Yes	79	100.0%	0	0.0%	79	100.0%
	No	71	100.0%	0	0.0%	71	100.0%
Cost	Yes	79	100.0%	0	0.0%	79	100.0%
	No	71	100.0%	0	0.0%	71	100.0%

3.4 Extreme Values Analysis

Looking at Table 5, overall cost group and lead time group, cases 92,119, 107 and 105 represent the lowest in overall cost and lead time groups; in fact, only the first two cases applied quality measurements. The research found that the four cases present companies that follow growth strategy[62]. Hence they tend to differentiate their services through reducing product prices and development time. Meanwhile, Case 12 represents the highest in overall cost and lead time. Research found that case 12 represent a company that applied quality measurements recently. Hence, quality measurement integration with ASD is not adequately realized in case 12. Looking at Table 5, Lead Time group, row "Yes", cases 12 and 98 represent the highest lead-time with the application of quality measurements. Case 98 represent a company that doesn't apply quality measurements in a strict matter. On the other hand, cases 92 and 119 represent the lowest lead-time with the application of quality measurements. After careful investigation, case 92 is not accurate while case 119 represent a company that applies quality measurements in a strict manner. In fact, this company has an effective ASD framework, which provides indications for the positive impact of quality measurements over ASD. On the other hand, looking at row "No" in overall cost group and lead time group, the values are heterogeneous because the four cases represent companies that don't standardize ASD. In fact, previous tests in section 2.3.2.6 showed that the data on overall cost group, group "No", is heterogeneous statistically. Hence, with absence of quality measurements, this inconsistency in cost estimation led us to infer the state of inconsistency in ASD processes. Indeed, this result also indicates how the absence of quality measurements affects ASD processes and consistency.

3.5 Independent T-test Results

Looking at overall cost row in Table 6, Levene's Test shows that p is value less than .05, which means that the variability in group "Yes" and "No" is not the same. However, looking at lead time row in table 6, Levene's Test shows that p is value greater than .05, which means that the variability in group "Yes" and "No" is about the same, for more information about homogeneity of variances, please refer to section 2.3.2.6. Looking at lead time group, according to Levene's Test results, the researcher chooses the values of the first row (bolded) while choosing the values of the

Table 5. Extreme values for the population sample

	Quality_Measurement			Case Number	Value
Overall Cost	Yes	Highest	1	12	$15,890
			2	44	$15,457
		Lowest	1	92	$1,623
			2	119	$2,559
	No	Highest	1	126	$44,733
			2	70	$43,065
		Lowest	1	107	$10,368
			2	5	$12,666
Lead Time	Yes	Highest	1	12	677
			2	98	640
		Lowest	1	92	76
			2	119	108
	No	Highest	1	52	820
			2	45	754
		Lowest	1	107	309
			2	5	367

second row (bolded) in overall cost group. Looking at the p value in both rows, the value of Sig. (2-tailed) is less than .05, which means that there is a statistically significant difference between Group "Yes" and group "No" and the differences between them are not likely due to chance. Consequently, $\mu_{cost1} \neq \mu_{cost2}$ and $\mu_{leadtime1} \neq \mu_{leadtime2}$; hence, the researcher rejects the null hypothesis and considers this result as a support to the alternate hypothesis. This means that we can infer statistically that it is more likely that using quality measurements decrease ASD lead-time and development cost in experiment scope. Consequently, there is evidence to support the proposition that quality measurements integration with ASD presents a strategic value to business organizations.

3.6 Validating the Independent T-test Results Statistically

Looking at Table 6 and Table 7, the mean difference values are within confidence interval, which suggests further validity for the results. Additionally, the research employed resampling using bootstrapping[63,64] to validate

Table 6. Independent t-test for equality of means

		Levene's Test for Equality of Variances		t-test for Equality of Means					
		F	Sig.	t	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
								Lower	Upper
Overall Cost	Equal variances assumed	40.966	.000	-17.930-	.000	$-16,340.545-	$911.360	$-18,141.503-	$-14,539.587-
	Equal variances not assumed			-17.318-	.000	$-16,340.545-	$943.559	$-18,213.391-	$-14,467.700-
Lead Time	Equal variances assumed	2.791	.097	-10.868-	.000	-206.180-	18.972	-243.671-	-168.689-
	Equal variances not assumed			-10.990-	.000	-206.180-	18.761	-243.258-	-169.103-

Table 7. Bootstrap for the independent t-test

		Mean Difference	Bootstrap[a]				
			Bias	Std. Error	Sig. (2-tailed)	95% Confidence Interval	
						Lower	Upper
Overall Cost	Equal variances assumed	$-16,340.545-	$2.433	$949.334	.000	$-18,238.349-	$-14,532.189-
	Equal variances not assumed	$-16,340.545-	$2.433	$949.334	.000	$-18,238.349-	$-14,532.189-
Lead Time	Equal variances assumed	-206.180-	.079	18.244	.000	-239.756-	-168.386-
	Equal variances not assumed	-206.180-	.079	18.244	.000	-239.756-	-168.386-

a. Bootstrap results are based on 2000 bootstrap samples

independent t-test results with 2000 bootstrap samples. Comparing Table 7 values against their counterparts in Table 6, the values are not significantly different, which also suggests further validity for the results of the independent t-test.

3.7 Selecting Machine Learning Algorithm

The researcher selected four different algorithms that reflect different learning methodologies. These methods are as follow:

3.7.1 Linear Regression

This algorithm tries to model the relationship between two variables or more through fitting a linear equation to the experimented data[65]. The researcher selected this model because of the simplicity of the observed data.

3.7.2 Multilayer Perceptron

Based on Neural Networks, Multi-Layer perceptron is essentially a feed forward neural network with multiple levels of perceptions between input and output layer[66]. This algorithm is able to model any complex relations between data variables.

3.7.3 K Star

Based on lazy learning, K star is an instance-based algorithm that determines the class of an instance through comparing it to the class of similar training instances[67].

3.7.4 Decision Stump

Based on decision trees, decision stump is a machine learning algorithm that is based on constructing a decision tree with one root, which is connected to its leaves[68]. Unlike many decision tree models, decision stump can predict numeric values.

These algorithms represent different machine learning methodologies. Using Weka experimenter[69] with 10-folds cross validation, the researcher selected linear regression as a baseline model and tested the rest of the models against it. Indeed, Table 8 shows the results of the tests.

Table 8 shows that the values of decision stump model are significantly worse than all other algorithms. Indeed, correlation coefficient is significantly lower than other machine learning algorithms while error values are higher than other algorithms. On the other hand, correlation coefficient for Multilayer Perceptron and Linear Regression is equal with no statistical significance. However, though not statically significant, error values for Linear Regression are lower than error values for Multilayer Perceptron. Accordingly, in accordance with the previous results and in the light of objective 3 and question 3, the researcher developed a DSS using linear regression model[70]. Linear regression analysis generates an equation that describes the quantitative relationship between one or more variables[71]. As discussed in section 2.2, experiment and survey design, the regression model accepts the application of quality measurements and lead time as input and generates overall cost as output.

Table 8. Comparing machine learning algorithms

Comparison Feature	Linear Regression (base)	Multilayer Perceptron	KStar	Decision Stump
Correlation coefficient	0.92	0.92	0.91	0.84 *
Mean absolute error	2938.03	3342.74	2985.86	4377.26 [v]
Root mean squared error	3977.00	4334.29	4153.18	5521.87 [v]
Relative absolute error	3977.00	4334.29	4153.18	5521.87 [v]
Root relative squared error	40.87	44.87	42.62	57.08 [v]

Table 9. Regression model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.914[a]	.836	.834	$4,032.874	1.987
a. Predictors: (Constant), Lead Time, Quality_Measurement. b. Dependent Variable: Overall Cost.					

Examining Table 9, R-square measures the level of fitness between the dataset and the regression model[72].

The R Square value for the model is .836, which implies that the regression model explains 83.6% of the variation in the statistical model. Accordingly, the researcher can infer that the model fits the data. In addition, the Durbin-Watson statistic[73] is approximately two, which means the size of the residual for one case doesn't affect the size of the next case. Consequently, the residuals are independent, which is a basic assumption for determining the validity of linear regression results.

Nonetheless, R-square cannot confirm the objectivity of the model predictions. Therefore, researchers use residual tests to confirm that[74] Figure 4(a) shows an approximate correlation between the model predictions and their actual results, which makes the researcher infer that the model fits the data. Side by side, Figure 4(b) shows that the residual points are tending to cluster around the symmetric line approximately, which provides further support for the validity of the model. However, the model may need further statistical treatment to improve accuracy in some areas.

After developing the regression model, the researcher developed a DSS based on that model. Figure 5 shows the online version of the DSS while figure 6 shows the desktop version of the DSS. The researcher developed the DSS using Microsoft VB.net 2.0 in the desktop version, and Microsoft ASP.net 2.0 in the online version. The program accepts the variables lead time, quality measurements, and outputs development cost. Developing this application answers the third research question in section 1.2, research questions, and achieves the third objective in section 1.3, research objectives. In fact, managers in Jordan can now use the DSS to evaluate and understand the impact of quality measurements over ASD, and provide assistance for ASD planning, scheduling, and budgeting. Furthermore, "section 6. Limitation, Delimitations, and Assumptions", explains how to interpret research findings.

The next section illustrates the research recommendations briefly.

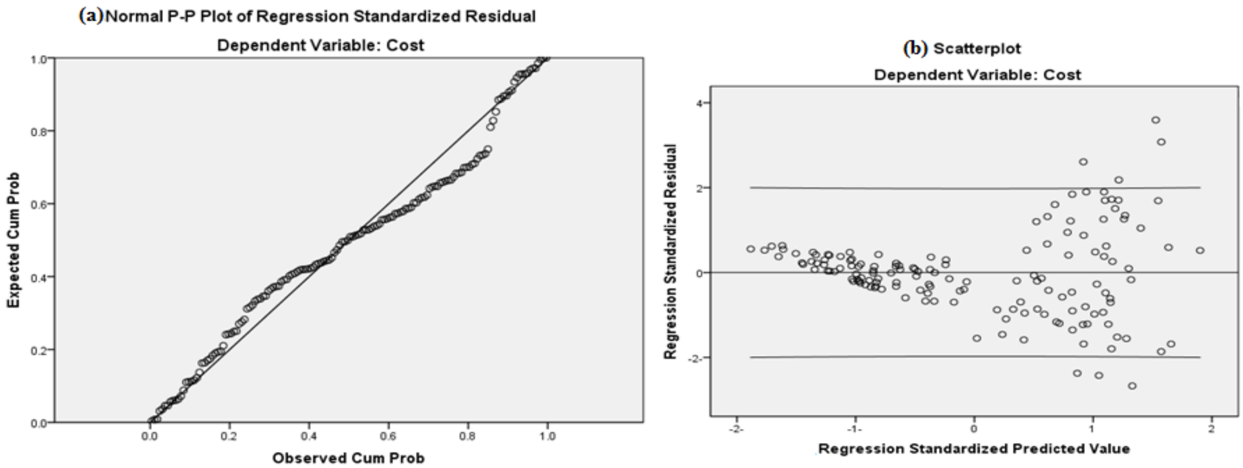

Figure 4. Residuals test plots.

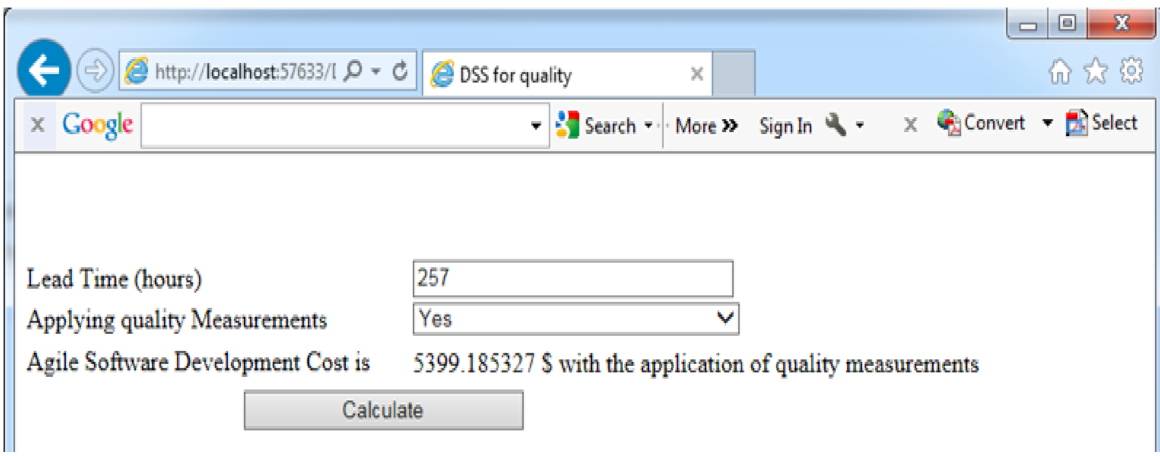

Figure 5. The online version of the DSS.

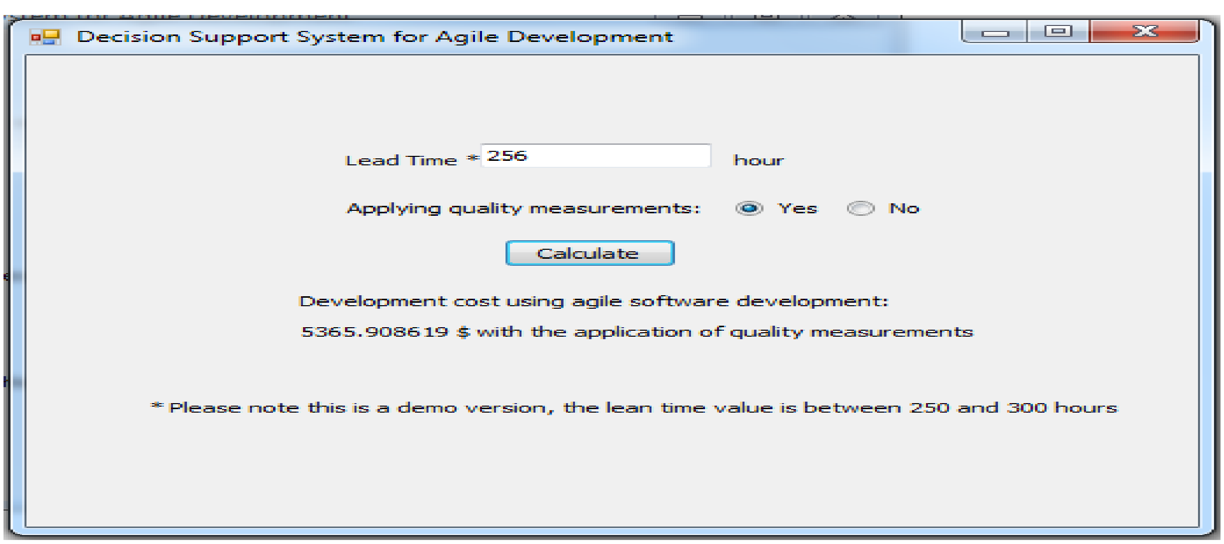

Figure 6. Desktop version of the DSS.

4. Recommendations

After completing the research stages, the research recommends the following:

- The research doesn't recommend the absence of quality measurements in ASD processes. Indeed, quality measurements play a fundamental role in improving and leveraging ASD processes.
- The research recommends aligning quality measurement application with the organizational strategy in order to use it as a key to strengthen and sustain the competitive advantage.
- The research recommends developing DSSs for measuring quality measurements effectiveness and maximizing its benefits.
- In Jordanian business environment, the research recommends using the developed DSS in order to evaluate and understand the process of integrating quality measurements with ASD. In fact, the DSS output provides valuable indications about the impact of quality measurements over ASD. Additionally, the DSS should be used to help in scheduling and planning ASD projects.
- Outside Jordan, the research recommends using the developed DSS search findings in order to understand the strategic implications of integrating quality measurements with ASD in empirical sense.

The next section lists research conclusions.

5. Conclusions based on Research Questions and Objectives

The section lists research conclusions with reference to research questions and objectives.

With regard to questions (1,2) and objectives (1,2), the research concludes the following:

- Quality measurements play a fundamental role in improving and leveraging ASD processes.
- The absence of quality measurements may lead to inconsistency in ASD processes.
- Quality measurements can be used as a key for developing a competitive advantage over competitors in ASD business environment.

With regard to question three and objective three, the research concludes the following:

- Regression analysis is suitable for estimating a simplified relationship between quality measurements and ASD continues variables. Indeed, the analysis process may show high R-squared value.
- Decision Support Systems can be employed to support aligning quality measurements application with organisational strategy.
- Decision Support Systems can be used to measure and evaluate the process of integrating quality measurements with ASD processes.

6. Limitation, Delimitations and Assumptions

In spite of the research contributions to narrow the research gaps, the results of research have some limitations, which require attention in interpreting, using, and applying the research findings. As the empirical data indicates, the limitations are as follow:

- This research was limited to IT organizations in Jordan. Indeed, the target population included managers from different IT levels in Jordan; hence, outside Jordan, the findings of this research require further studies in order to be generalized with IT organizations that have similar structure with Jordanian IT organizations.
- The developed DSS can be used as an empirical tool to understand the relation between quality measurements and ASD. However, though the model explains a large amount of variation that does not imply that it can predict well on unseen data, which requires further research.
- Due to the frequent filtering of unsolicited e-mail, the initial contact with participants was through mobiles, requesting their participation in the study.
- The researcher was not able to develop the research more broadly because the limitations of literature, reflecting research gaps in this research area.
- Since many machine learning algorithms are not regression algorithms or couldn't predict a continuous target variable, the researcher had to test a limited number of algorithms, which are identified in Table 8.

In addition to limitation and delimitations, the study made the following assumptions:

- Participants responded honestly.
- Each participant had adequate knowledge in ASD project planning.
- Participants were experienced enough to predict ASD project cost and development time based on the project proposal.
- Respondents were able to read, analyze, and comprehend project proposal and respond accordingly.

7. Future Works

The researcher is planning to conduct the following activities in the future:

- Expand the population sample in order to expand the range of the statistical generalizations. Indeed, the population may include other countries.
- Publishing the developed DSS online and testing it using a dedicated questionnaire. Additionally, improve the DSS according to feedback from users.
- Conduct a study to measure the impact of using the developed DSS.
- Using the research study to develop other DSSs for supporting the process of integrating quality measurements with ASD.

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Appendix-A, Consent to Act as a Research Subject

The researcher is conducting a research study entitled, "An Empirical Study to Develop a Decision Support System (DSS) for Measuring the Impact of Quality Measurements over Agile Software Development (ASD)". The main goal of the research study is to develop a Decision Support System (DSS) for measuring the impact of quality measurements over Agile Software Development (ASD).

Interviewee:

I, _______, a current or former employee in ____, Agree to participate in this research study voluntary, and according to the following conditions:

1. I may reject to participate and/or withdraw from the study at any time and without consequences.
2. The anonymity of my contribution will be preserved.
3. The results and implications of the research will be published.
4. OSAMA ALSHAREET (researcher) will explain the research to me and answer my questions.
5. The participant must be aware of his contribution in advance (time, length, and place).

By signing this form, I agree that I understand the nature of the study, the implications of participating in it, and the means by which my anonymity will be preserved. My signature on this form also indicates that I give my permission to voluntarily act as a participant in this research study.

Signature of the interviewee _______ Date _______

Signature of the researcher _______ Date ________