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Effects of Data Exchange Methods on Perceived Risk and Trust in Digital Engineering

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Abstract. Data exchange is a critical part of collaborative design and digital engineering. Design teams need effective communication to exchange vital information and achieve desired outcomes. Literature shows high data quality is matched with higher levels of trust and lower levels of perceived risk which influence design decisions. This paper conducts a survey of industry professionals as a preliminary investigation of how data exchange methods implemented in digital engineering affect perceived trust and risk levels of engineers. The survey adopts questions from the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT2) questionnaires to measure risk and trust perception in digital engineering environments for three data exchange methods and interfaces: direct data integration, air-gapped import and export, and semantic data exchange. Survey results show engineers have different trust and perceived risk levels towards different data exchange methods. Engineers behavioral intentions towards using a data exchange method depend on perceiving the method as less risky and trustworthy. Understanding how data exchange methods and interfaces impact engineers' trust and risk perception can inform effective implementation of digital engineering and lead to more successful collaborative engineering design projects.

Keywords. Collaborative Design Environments, Digital Engineering, Engineering Teams, Data Exchange, Risk, Trust

Introduction

Contemporary engineering deals with large-scale projects with high levels of complexity. Digital Engineering (DE) aims to overcome design and development challenges to create efficient, complex systems and systems-of-systems. For example, the design of a satellite requires an engineering team to complete various complex tasks in every stage of its lifecycle. Engineers must ensure the technical demands of their sub-systems and the entire integrated system are met while managing design and maintenance constraints. This leads to constant interaction and information flow both within and between subsystems. Engineers need to rely on the data they receive to deliver expected outcomes for a task, making the data exchange process critical for collaborative engineering systems.

The quality of received data impacts the engineers' trust and perceived risk in using the data to complete their tasks [1, 2, 3]. High-quality data decreases perceived risk and

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increases trust levels towards using the data. The shift in engineering practice to DE changes how engineers receive data, which might have different impacts on engineers' trust and perceived risk levels for the data.

This paper investigates engineers' trust and risk perception towards three selected data exchange methods (DEMs) in DE environments: direct data integration, air-gapped import and export, and semantic data exchange. A survey of industry professionals (from a related STEM field with an average of 17.3 years of experience) with questions based on the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT2) questionnaires measures perceived risk and trust levels. Understanding how engineers perceive DEMs can help identify preferences and design more effective DEM leading to more successful collaborative engineering systems.

1. Background

1.1. Digital Engineering

DE creates computer readable models that represent all aspects of the system and supports design, development, manufacture, and operation activities throughout its lifecycle. DE can improve communication, facilitate design trade-space evaluation capabilities [4] and develop innovative and effective solutions in a virtual environment.

Increased complexity in engineering products can require hundreds to thousands of engineers and engineering teams from different disciplines to work together in parallel tasks simultaneously [5]. Satellites are an example of a complex engineering product where multiple cross-functional teams work together [6, 7], meaning there are often many physical components and design participants [8]. Multi-disciplinary engineering teams rely on input information from other engineers achieved through data exchange [9]. However, the data exchange process is challenging because data produced by each engineering team is specific to their disciplines produced by diverse software tools [10]. Data heterogeneity in collaborative engineering processes requires interoperable applications that exchange both the data and the data semantics [11, 12, 13]. Data integration is a pre-requisite for supporting collaboration among multi-disciplined engineering teams to overcome heterogeneity and create a common view of the data [14].

1.2. Data Exchange Methods

The literature identifies many data exchange methods to make the collaborative engineering process more efficient. Earlier research identifies the necessity of modeling the design process to perform tasks in parallel for concurrent engineering [5]. This perspective focuses on modeling the engineering tasks prior to managing information flow by designing the process with identification and allocation of dependent, independent, and interdependent tasks [5]. This technique depends on human activities and coordination of tasks by managing human interactions and information flow [15].

Data integration enables the exchange of knowledge across heterogeneous data sources to achieve semantic interoperability [16]. There are various perspectives in the literature to identify different data integration processes. Some studies suggest developing local independent ontologies and then mapping them into a global ontology to bridge the exchange and integration of data across different teams and organizations [17]. Others suggest a single ontology that semantically integrates data from several data sources to track engineering tasks [18]. Hennig et al. suggest creating a data exchange standard as a common data model for single ontology data integration. Lee and Kim also propose a semantic technology with a single ontology to exchange context information from several data sources [19]. Other literature investigates multiple ontology approaches to represent various data sources, store information in local ontologies, and then orchestrate local ontologies to build various applications [20] using linked data to produce software applications in the production system environment.

Based on the literature review, the SERC research roadmap for Digital Engineering [21], and the second author's experience in industry, this paper investigates three DEMs illustrated in Figure 1 ranging from manual to automated processes. Air-gapped import and export represents earlier perspectives in data exchange processes that involve modeling and coordinating tasks that are dependent on human actions. Direct data integration is commonly used in industry to directly enable data exchange between data sources. Finally, as it holds a major place in literature [10, 11, 12, 13, 18] but is not yet in widespread use in industry, semantic data exchange enables data exchange among sources using globalized data transformation processes.

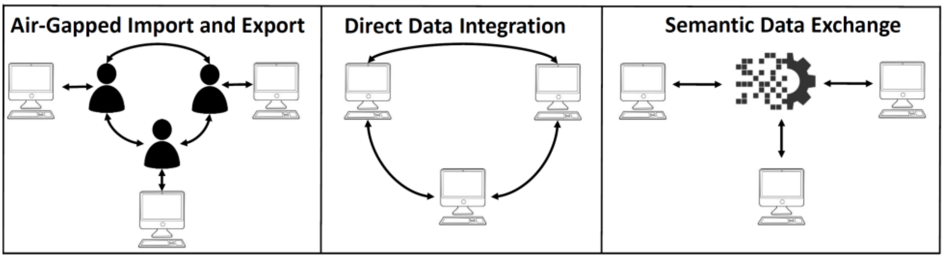


Figure 1. Selected DEMs: air-gapped import and export, direct data integration, and semantic data exchange.

Air-gapped Import and Export (AG) uses one or more intermediate data structures to write data out of one tool environment and read into another tool environment. A human user or users participate in both export and import processes, possibly with different users for each process. This type of export and import between environments and usage of intermediate data structures creates a gap between the tool environments where data format translation is required to convert from one tool (the export) to the other (the import).

Direct Data Integration (DI) involves point-to-point data connections between tools without the need for an intermediate data construct. Data may be pushed or pulled from one tool to another based on an established interface using a script, API, or established connections provided by tool vendors or other third-party vendors. The data exchange process does not have intermediate steps to represent data in a new environment. The human interaction with this method is in establishing the point-to-point connection.

Semantic Data Exchange (SDE) involves a semantic database environment that can identify the data constructs in tool environments and make the data available to other tool environments based on an underlying ontology. This method does not depend on APIs or point-to-point connections between specific tools. This method relies on an ontology to describe the data in the environment and the different tools that may need to access and exchange the data. Human interaction in this method focuses on the ontology development and continued evaluation of the ontology for necessary growth.

1.3. Data Quality Effects on Perceived Risk and Trust

Dong identifies communication as the recipe for a successful team [21] because engineers need to communicate technical demands and constraints [8], making data exchange a vital factor for system success. Literature shows data quality affects how the engineers view received data [1, 2]. As engineers face a high volume of information, they are obligated to decide what to use based on perceived quality. Criteria that affect data quality include accuracy, currency, coverage, and believability [2, 22, 23]: accuracy is the extent to which information is free from error, currency is the degree to which the information is up-to-date rather than obsolete, coverage is the completeness of the information, and believability is the extent to which the information is plausible [2].

Information science and management science investigates how data quality affects trust and perceived risk, which subsequently influences the data exchange success [1, 2]. Kelton et al. states trustworthiness of information can be evaluated by its accuracy, objectivity, validity, and stability [2], which suggests engineers base trust on several criteria. Nicolaou et al. find evidence that information quality affects trust and perceived risk. High quality of information is matched with higher levels of trust and lower levels of perceived risk, and decision-makers' intention to use received information changes based on these levels [1]. Alternative DEMs in digital engineering might provide different information quality, affecting engineers' trust and perceived risk.

2. Research Objective

Existing research in information and management science investigates how information quality affects trust and perceived risk levels in inter-organizational systems [1, 2]. This background focuses on strategic collaborative relationships and user perspectives versus our desire to look at intra-organizational systems within project teams. Several DEMs have evolved over time in DE that can impact perceived data quality by engineers, thus changing trust and risk perceptions. However, there has not been a study in collaborative systems engineering or the DE domain that investigates how DEM impacts engineers' perceived trust and risk levels, the subject of this paper. Literature also suggests demographic factors such as experience, education, age, and gender might affect trust and perceived risk; however, investigating these factors is out of the scope at this time.

More specifically, this paper investigates three research questions asked of DE, also illustrated in the logic model (Figure 2):

1. How do DEMs affect trust and perceived risk levels?
2. How does trust for a DEM affect behavioral intention towards it?
3. How does perceived risk for a DEM affect behavioral intention towards it?

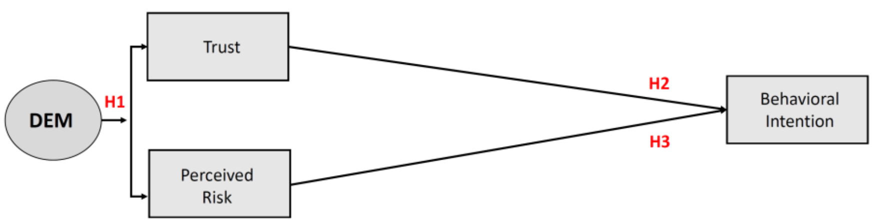


Figure 2. Logic model showing hypothesis paths adapted and modified from UTAUT2 model.

3. Study Methodology

3.1. Survey

This paper uses a survey which adopts questions from the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT2) questionnaires to measure trust (T), perceived risk (PR), and behavioral intention (BI) in digital engineering environments for each DEM [25, 26, 27]. Participants completed a two-part, anonymous, online survey. The first part includes nine screening questions to collect standard demographic information to characterize the population. The second part includes 28 standard item assessment questions, including 27 5-point Likert scale (‘*Definitely disagree*’ to ‘*Definitely agree*’) questions and one open ended question.

The survey has subsections for each DEM with questions to measure dimensions of trust, perceived risk, and behavioral intention. Where trust and perceived risk parcels investigate perceptions of participants towards the method, behavioral intention measures their intention of using the method. Three questions in each dimension measure internal consistency. Questions are given in a randomized order in each subsection. Sample questions for each dimension of the DDI method include:

- DDI-T3: “I will trust the information I receive via a direct data integration.”
- DDI-PR2: “Using a direct data integration method exposes design and development tasks to an overall risk.”
- DDI-BI1: “Assuming I have the infrastructure to use direct data integration, I intend to use it for information exchange.”

3.2. Demographics

Prior to the experiment, survey items collect demographic information including age, gender, English language ability, education, and experience levels. 23 participants (3 female and 20 male) completed the survey. Participants ranged from 26 to 79 years of age. 16 participants reported they are native/fluent English speakers, 6 participants reported TOEFL (>90) or IELTS scores (>7.5) and 1 participant reported TOEFL (<60) or IELTS scores (<7). Experience in a STEM-related field ranged from 0 to 40 years with an average of 17.3 years. Participants reported education in a STEM related field ranging from 4 to 12 years including undergraduate and graduate studies with an average of 6.8 years. The survey does not directly gather data about familiarity with the selected DEMs, but the survey recruitment was posted via a professional networking website to target participants who are industry professionals working in a STEM-related field.

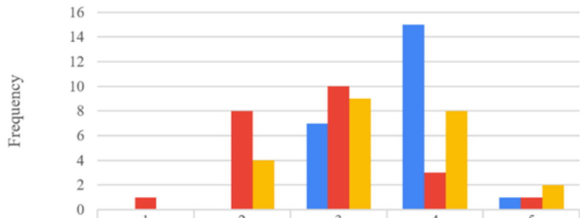
4. Results

The 5-point Likert scale responses were converted to number scales for measurement ranging from 1 (Definitely disagree) to 5 (Definitely agree). High scores indicate higher trust, higher perceived risk, and higher behavioral intention for using the method. Statistical analysis uses an average of three responses for each dimension. Out of 621 responses for 5-point Likert scale items, two responses are missing: one from DDI-T3 coded items and one from SDE-PR3 coded items. For those participants’ responses, the average of two available items are calculated.

To check internal consistency of items, Cronbach's alpha (α) is calculated for each dimension of each method. All the items except the DDI-PR have α > 0.7, establishing sufficient consistency for analysis. Analysis using data from DDI-PR cannot make any statistical conclusions because this item does not have internal consistency and is therefore excluded from the results covered here.

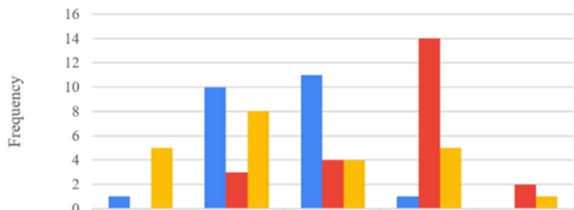
4.1. Effect of DEM on Trust and Perceived Risk

One-way ANOVA analyzes measured trust and perceived risk levels across the three DEMs. Results show a statistically significant difference between measured trust (p-value=0.0006) and perceived risk (p-value= 1.45E-04) of participants. ANOVA analysis for the PR dimension omits the DDI method to only investigate differences between AG and SDE methods because DDI-PR data lacks internal consistency. Results show participants trust the DDI method the most (average = 3.94) and the AG method the least (average = 3.01). They perceive the AG method as the riskiest method (average = 3.94) and the SDE method as the safest method (average = 2.80).



	1	2	3	4	5
DDI Trust	0	0	7	15	1
AG Trust	1	8	10	3	1
SDE Trust	0	4	9	8	2

Figure 3. Histogram of measured trust level for each DEM.



	1	2	3	4	5
DDI Risk	1	10	11	1	0
AG Risk	0	3	4	14	2
SDE Risk	5	8	4	5	1

Figure 4. Histogram of measured perceived risk for each DEM.

4.2. Effect of Trust on Behavioral Intention

Table 1 shows significant positive correlations between trust and behavioral intention dimensions for all methods. Three simple regression models further statistical analysis. Results in Table 2 show a statistically significant relationship between trust and behavioral intention dimensions for all methods. Figure 5 illustrates the positive relationship where higher trust is associated with more intention of using that DEM.

Table 1. Correlation between trust, risk, and behavioral intention for each method.

	DDI-T	DDI-BI	
DDI-T	1		
DDI-BI	0.619	1	
	AG-T	**AG-PR**	**AG-BI**
AG-T	1		
AG-PR	-0.542	1	
AG-BI	0.621	-0.340	1
	SDE-T	**SDE-PR**	**SDE-BI**
SDE-T	1		
SDE-PR	-0.811	1	
SDE-BI	0.577	-0.451	1

Table 2. Regression results for the effect of trust on behavioral intention for each method.

	Coefficient	Std. Error	t-stat	p-value
DDI-BI ~ DDI-T	1.212	0.336	3.608	0.002
AG-BI ~ AG-T	0.729	0.201	3.627	0.002
SDE-BI ~ SDE-T	0.631	0.195	3.234	0.004

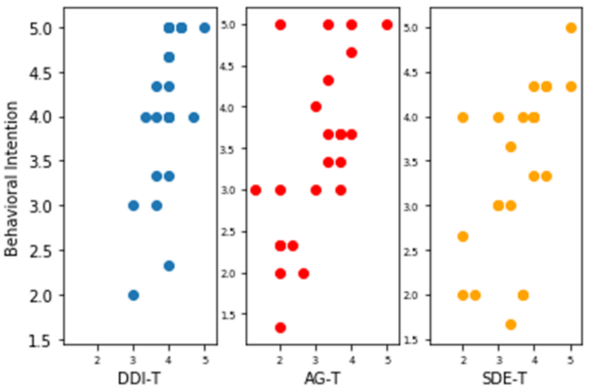


Figure 5. Scatter plots comparing trust and behavioral intent for each method.

4.3. Effect of Perceived Risk on Behavioral Intention

Table 1 shows a significant negative correlation between perceived risk and behavioral intention dimensions for all methods. Two simple regression models perform further statistical analysis. Results in Table 3 show a statistically significant relationship between perceived risk and behavioral intention dimensions for SDE method. However, results show no statistically significant relationship between measured perceived risk and behavioral intention for the AG method. Figure 6 illustrates the relationship where higher perceived risk tends to lower intentions for using that DEM.

Table 3. Regression results for the effect of perceived risk on behavioral intent for each method.

	Coefficient	Std. Error	t-stat	p-value
AG-BI ~ AG-PR	-0.477	0.288	-1.658	0.112
SDE-BI ~ SDE-PR	-0.403	0.174	-2.315	0.031

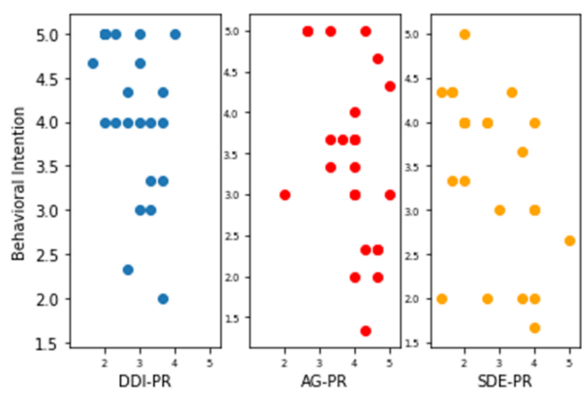


Figure 6. Scatter plots comparing perceived risk and behavioral intent for each method.

5. Discussion

5.1. Implications for Digital Engineering

While this is an initial survey with a limited dataset, these preliminary trends are informative regarding perceived trust, risk and behavioral intent among the three DEMs considered. The general findings show participants have higher intentions to use an exchange method if they perceive it as trustworthy and less risky, which aligns with literature [5, 6, 7]. Before discussing results for each DEM, it should be noted that the main goal of the paper is not to favor a specific DEM but to show importance of perceived data quality so future studies can consider this aspect while developing DEMs.

Results show that respondents have a high trust in the direct data exchange method and intend to use it if available. This is also reinforced in a low perceived risk, though additional data points are required to determine if the perceived risk of the direct data exchange method is statistically significant. This is promising for DE development and implementation as the first steps on DE implementation roadmaps move from air gapped import/export exchange methods towards direct data integration. The high trust correlated with the intent to use direct data exchange suggests it is being implemented more widely and is recognized in practice as a preferred and trusted means for exchange.

The air gapped method has the lowest average perceived trust and highest average perceived risk of the methods evaluated. It has the lowest average behavioral intent, but also high variability, suggesting it may still be a widely exercised option for data exchange, even if it is perceived as risky and not trustworthy. This aligns with the commonly held belief that more human touch time moving data from one source to another creates a greater chance that errors are introduced and propagated, resulting in unreliable solutions. This is the data exchange method that DE methodologies seek to replace as part of the digital transformation to enable data availability to more users without the potential for introducing human errors.

Semantic data exchange was perceived as a more trustworthy exchange method than air gapped exchange, but not as trustworthy as direct data exchange. This could be attributed to the limited exposure and availability of this method, as it is the newest method and not utilized as widely in industry yet. This would also align with a lower behavioral intent as it is not perceived to be ready for implementation at this time. As this method is still under active development as part of digital transformation efforts, it is intriguing that it scored above other methods that are more commonly experienced and utilized in industry. It is important to see statistical significance that semantic data exchange is seen as a trustworthy source for data exchange, though it is more telling of the current state of practice (or lack thereof) that is still perceived as high risk as the semantic methods themselves are still in development.

5.2. Limitations

Results from this study are subject to several limitations. First, the sample size is small, and the statistical analysis reflects results only for the selected population. Results might show variations in a larger sample size or a different sampled population. Second, the survey does not collect information about the knowledge level of participants towards the selected DEMs; participants' responses might change based on their experience and comfort level. Third, analysis does not include any DDI method PR dimension because data from this group does not have internal consistency and therefore has been excluded in the analysis section. Lastly, although the paper shows significant results for the relationship between demographic factors and trust and perceived risk dimensions, there is a high correlation between these factors, so a larger sample size and more detailed statistical analysis are required to make a statistically significant conclusion.

6. Conclusion

This study concludes that engineers have different trust and perceived risk levels towards different data exchange methods from the sampled population. The data provides statistically significant evidence that trust and risk perceptions affect behavioral intentions towards using DEMs. Results also suggest that the availability of and exposure to technology is a key factor determining the behavioral intention. Analysis results show that demographic factors have a significant effect on trust and risk perception. Due to limitations in the dataset, further analysis is required to produce more explanatory conclusion about how and why demographic factors influence engineers' trust and perceived risk levels towards different data exchange methods. A future study with a larger sample size can provide further evidence and more significant statistical results.

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