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How Can Business Analytics Induce Creativity: The Performance Effects of User Interaction with Business Analytics

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HOW CAN BUSINESS ANALYTICS INDUCE CREATIVITY: THE PERFORMANCE EFFECTS OF USER INTERACTION WITH BUSINESS ANALYTICS

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DEDICATION

To

My parents, my wife, and my kids

This Research is dedicated to my parents, my wife and my kids, who encouraged me and helped me do this research. Special feelings of thanks to them as they always pray for me and encourage me to work hard.

My Parents: Thank you for your love and support throughout my life. I learned passion, dedication, and caring from you. I am blessed to have you as my parents. I cannot thank you enough nor give you back a small portion of what you have given me, I love you.

My Wife: Thank you for believing in me, for supporting my knowledge journey, and for your patience throughout this project. I will encourage you and support you in your studies. No words can do justice, I love you.

My kids: You inspired me to do more and go after a doctoral degree. Persistent and continued learning is the message I want to pass to you through this work. I love you all.

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ABSTRACT

Most organizations today use business analytics systems mainly for efficiency; reducing cost by contacting the right customer, generating revenue by reducing churn, etc. Nevertheless, business analytics holds promise in generating insights and in making users more creative in their decision making process.

Analytics technology is becoming sophisticated with very advanced technical capabilities. However, behavioral aspects (i.e. user interaction) of using business analytics software have not reached the same level of sophistication. Very little research in this field discusses how to implement analytical systems and what outcomes will it produce.

We are looking at conditions that can enhance user interaction with business analytics systems leading to certain performance outcomes. We propose that the fit between users' cognitive style (intuitive vs. rational), business analytics model representations (decision tree vs. clustering), and task type (convergent vs. divergent) can lead to efficiency but can have adverse effects on creativity because that might lead to mindlessness in the decision making process.

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CHAPTER I

INTRODUCTION

Business analytics has emerged as a hot topic and is widely seen as the next big trend in the information system field. Business Analytics is defined by Davenport (2010) as "the broad use of data and quantitative analysis for decision making within organizations. It encompasses query and reporting, but aspires to greater levels of mathematical sophistication." In a study done by The Data Warehouse Institute in 2009, "Advanced Analytics" was identified as having the highest growth in next generation trends.

The research report that appeared in MIT Sloan Management Review in fall 2011 discussed the role business analytics can play in attaining competitive advantage and the widening divide between companies who embraced business analytics and the ones who did not (Kiron, Shockley, Kruschwitz, Finch, & Haydock, 2011). One of the keys to business impact lies in the ability to turn analytics into insights that results in business action (Harriott, 2013). Davenport (2010) emphasized that analytics should help generate insights and design strategies that can help companies achieve competitive advantage.

Researchers have stressed the need to turn analytics output into actionable insights (Fayyad & Uthurusamy, 2002), (Pearson, 2012). Nevertheless, that is not happening today because of different challenges facing analytics in unlocking insights (S. E. Arnold, 2013). Wilson (2009) notes that "turning analytics into insights is still a rarity, even in the US."

Business analytics systems sit at the top of the information systems hierarchy. Information systems at the lowest level of the hierarchy should help users with automation and efficiencies of business processes (Laudon, Laudon, & Brabston, 2012). Information systems at the highest level of the hierarchy should help users generate insights and be creative in uncovering the future and designing strategies. Research in this area, however, has tended to look at efficiency as the performance effect of business analytics and decision support systems. Therefore, it is imperative that we research conditions that help business analytics users generate insights and become creative in their decision making.

Business analytics software is becoming sophisticated with very advanced technical capabilities. Nevertheless, the behavioral aspects (i.e. user interaction) of using business analytics software have not reached the same level of sophistication. Very little research in this field discusses how to implement analytical systems and what outcomes these systems will produce. In short, the human interaction with these new software technologies can have surprising and unpredictable results.

Practitioners have pointed out to the fact that user interaction and behavioral aspects are the major challenges facing implementations of business analytics. Fayyad (1996) identified user interaction and prior knowledge as major challenges to business analytics deployment. They highlight the challenge of creating environments that can help users achieve their goals through matching appropriate tools and techniques. They also recommend a focus on human-computer interaction rather than automated systems. Researcher has noted how analytics users are increasingly asking the question of how to turn discovered information into action (Kohavi, Rothleder, & Simoudis, 2002). The main issues reported show that current solutions are very technical and users find it difficult to understand the outcome and what to do with it.

Academics have also pointed to the same challenges. "The form of output is yet another challenge. The inputs to advanced analytics include immense amounts of data but the output needs to be simple, concise, readable, and usable. Finding or designing a system that is able to analyze the data and return output in a way that is valuable to the end-users is extremely important"(R. Bose, 2009). "Since data mining usually involves extracting "hidden" information from a database, this understanding process can get somewhat complicated. Because the user does not know beforehand what the data mining process has discovered, it is much bigger leap to take the output of the system and translate it into an actionable solution to a business problem"(R. Bose, 2009).

Coll (1991) posit that the reason for the degrading effect of DSS on decision quality in several cases was that DSS systems are not deployed appropriately, and that user's feel implicit criticism of their human abilities working with DSS systems. This is an indication that there is a lack of fit between user's and DSS systems, and that DSS deployment process need to incorporate different – not only technical but also behavioral – factors and enhance user interaction. Kriegel (2007) identified usability in business analytics as a major challenge and pointed to the fact that users do not understand analytics algorithms and patterns. Additionally, researchers posit that the reason behind deployment process failure is the failure of systems to allow managers to make decisions their own way (De Waele, 1978). As a result many managers complain that DSS systems are hard to understand, learn, and use (Sprague & Carlson, 1982).

Designers of business analytics investigate the data structure to decide on the best analytics methodology to use. Focusing on the data structure and not giving proper attention to the user's cognitive style and the task in hand, makes designers of business analytics lose sight of the ultimate goal of business analytics which is to induce creativity and generate insight. We are proposing that designers should investigate user's cognitive style and the task in hand to decide on the best analytics methodology to use.

In a latest article of IEEE computer graphics and applications, Choo (2013)argued the same thing:

> "Researchers who design computational methods must realize that making an algorithm more interactive and interpretable in practical data analysis scenarios is just as important as addressing practical concerns such as the data's maximum applicable size, computation time, and memory requirements."

Researchers are developing the "Business Analytics Capability Model" that guides organizations in enabling BA to create value for organizations. Establishing a sound foundation of high quality, usable, and integrated data creates an enterprise BA capability. Organizations should focus their attention on three dimensions: people, process, and technology in order to turn this data into insights that drive business decisions (Wixom, Yen, & Relich, 2013). Empowering users across the organization with pervasive, predictive real time analytics enables the transformation of insights (Nastase & Stoica, 2011).

Cognitive fit theory (CFT) provides a theoretical foundation of user interaction with business analytics and the interaction effect on performance. We need to understand three important dimensions of user's interaction with business analytics: task, user, and technology. CFT can be used to show how fit between these variables leads to efficiency in decision-making outcomes. The models developed show that a match between the technology, the user, and the task will make decision making process more efficient. A mental model will be constructed easily when the match exist which helps decision maker in finding the solution.

Although cognitive fit research mainly addresses efficiency has not explored other performance effects such as creativity, the absence of cognitive fit may help us understand situations that will produce other outcomes. Not having a cognitive fit might not necessarily be a bad thing. Mindfulness research suggests that disrupting the mental model of the decision maker can help in immersing the decision maker in the current problem and to think thoroughly of the situation (E. J. Langer & Piper, 1987). While mindfulness might degrade efficiency, the benefit may be to spur more creative solutions by the user. We integrate mindfulness theory with CFT in our research model in order to explore cognitive fit effects on creativity outcomes and insights generated through analytics.

Cognitive fit research has focused on symbolic and spatial output across simple tasks and complex tasks. Predictive analytics methodologies produce output that is different than the traditional business intelligence reporting output. Therefore, we will use decision trees and clustering as the two business analytics outputs. Decision trees exemplify the symbolic type of output, and clustering exemplifies the spatial type of output. The types of questions addressed with analytics move beyond simple and complex tasks. The tasks that will be tested in our research are convergent and divergent processes. These types of tasks allow us to examine creativity in a more direct way.

In order to be complete in our understanding of user interaction with business analytics and the performance effects, we will explore other potential causal mechanism that can have an influence. Cognitive experiential self-theory and technology frames of reference can shed light on the causal mechanism. Cognitive fit assumes that all users will experience fit the same way. Users differ in the approach they take to arrive at a decision. Several researchers stressed that individual user characteristics should play an important role in designing DSS systems (McKenney & Keen, 1974), (Davis & Olson, 1985). Vessey (1991) acknowledges that decision maker's use different processes in different type of tasks, but individual decision making styles are not included as part of CFT. Cognitive styles are an individual's consistent approach to organizing and processing information during thinking (Epstein, 2003). Cognitive experiential self-theory identifies two prominent approaches used by users to make a decision; experiential and rational (Epstein, 2003). Our research will explore how cognitive style influences cognitive fit effect on performance.

Technology frames of reference describe the non-contextual factors that work in the background and provide facilitating and restraining effects. Cognitive fit theory examines context specific cognitive components of the problem that directly affect the understanding of the problem; while frames of reference examines surrounding cognitive factors that work in the background and have both facilitating and restraining effects. Cognitive fit looks at the mental model of the elements in the current situation; while technological frames of reference look at the mental model of the situation itself.

Research Question

Our research is looking at conditions that would make user interaction with business analytics improve insights generation (creativity).

We are investigating whether the fit between clustering output and divergent type of task, or between decisions trees output and convergent type of task, have a negative influence on creativity, and if the absence of this fit have a positive influence on creativity. We will also explore if cognitive style and analytics frames of reference amplify the above identified influences.

The first section will include a review of relevant research and theoretical foundation and will identify the research gap in extant research. The second section will give a definition of the variables used in the model. The third section will introduce the model. The fourth section will discuss the methodology proposed to test the model. The fifth section will go through research implication and then practical implications. At the end the conclusion will summarize the findings.

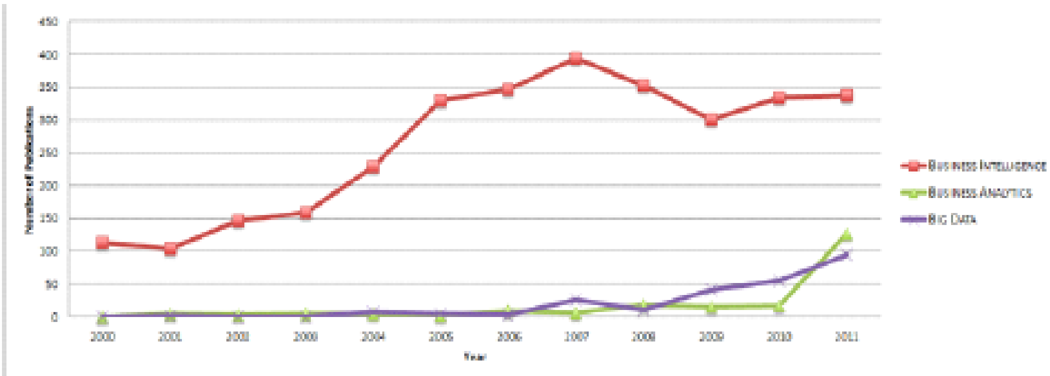
CHAPTER II

LITERATURE REVIEW

2.1 Business Analytics

Business analytics (BA) is a hot trend in computing and the number of books, white papers, webinars, and research reports indicate its importance (Watson, 2011). In late 1980s and early 1990s data warehousing and business intelligence (BI) were hot and BI was the umbrella term for technologies, processes, and applications that support decision making; nowadays, analytics is the umbrella term (Watson, 2011).

Big data is also hot and is changing the scope of BA. Organizations are trying to tap into structured and unstructured data sets coming from new sources like social networks, documents, emails, call centers, and websites. Software vendors are creating new generation business analytics that can be used with big data to deliver insights. Figure 1 below shows the rise in business analytics and big data in related research publications between the years 2000 to 2011.



Keyword	All Years	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
Business Intelligence	3,146	113	104	146	159	229	330	346	394	352	201	334	338
Business Analytics	213	0	5	43	4	5	2	9	6	19	16	17	126
Big Data	243	0	1	0	0	7	4	3	26	11	41	44	95
Total	3,602	113	110	149	163	241	336	358	426	382	358	356	560

Figure 1: Business Intelligence and Analytics Related Publication Trend from 2000 to 2011 (Chen, Chiang, & Storey, 2012)

"Business analytics systems encompass the people, processes, and technologies involved in the gathering, analysis, and transformation of data used to support managerial decision making" (Cosic, Shanks, & Maynard, 2012). BA systems were defined by Negash (2004) by the use of advanced statistical analysis tools to discover patterns, predict trends, and optimize business processes.

"Business analytics allows organizations to face forward, bringing insight to transformative decisions" (Nastase & Stoica, 2011). It benefits all aspects of an organization's value chain, including: inbound logistics, operations, outbound logistics, marketing and sales, and service" (Nastase & Stoica, 2011).

The following are categories of analytics (Watson 2011):

- Optimization analytics: mathematical programming like linear and integer programming, and simulation.
- Predictive analytics: decision trees, CART, generic algorithms, and neural networks.
- Descriptive analytics: data visualizations, dashboards and scorecards, drillable OLAP reports, published reports, SQL queries.

Another interesting categorization of business analytics that is used by practitioners is: Data analysis and Traditional BI, and advanced analytics.

- Data Analysis and Traditional BI: “BI systems combine data gathering, data storage, and knowledge management with analytical tools to present complex internal and competitive information top planners and decision makers.” (Negash, 2004). Traditional BI uses reports, dashboards, and visualizations to look at historical events which can inform decision making process.
- Advanced Analytics: “The overall process of turning low-level data – database, textual, and Web – into high-level knowledge by extracting patterns or models from observed data. The mining of data in these three forms uncovers patterns in them using predictive techniques” (R. Bose, 2009).

A number of analytics software's are available in the market today. Louridas and Ebert (2013) provided a list of the most popular statistical analysis shown in table 1. Their list shows how these software tools differ in terms of statistical sophistication required from their users, ease of use, and whether they are primarily stand-alone software packages or programming languages with statistical capabilities.

An overview of available software for statistical analysis.

Software	Expertise level	Focus	Environment	Platforms	License	URL
D3 (Data Driver Documents)	Medium	Visualization	Programming	Web-based	Open source	http://d3js.org
IBM SPSS	Medium to high	Statistics, data mining, and academic research	Stand-alone	Microsoft Windows, Linux, and Mac OS X	Pro-prietary	www.ibm.com/software/analytics/spss
Matlab	Medium to high	Numerical computation	Stand-alone/programming	Microsoft Windows, Linux, and Mac OS X	Pro-prietary	www.mathworks.com/products/matlab
Mathematica	Medium to high	Mathematics (analytical computation)	Stand-alone/programming	Microsoft Windows, Linux, and Mac OS X	Pro-prietary	www.wolfram.com/mathematica
Microsoft Excel	Novice	General purpose for office use	Stand-alone/programming via Visual Basic	Microsoft Windowsand Mac OS X	Pro-prietary	office.microsoft.com/en-us/excel
Python	Medium	General-purpose language for extensive scientific libraries (NumPy and SciPy for numerical computing and statistics, and Pandas for data handling and time-series analysis)	Programming	Many	Open source	www.python.org
R	Medium	Statistics, data mining, and academic research	Programming	Many	Open source	www.r-project.org
SAS (Statistical Analysis System)	Medium to high	Statistics, data mining, and academic research	Stand-alone	Server tier on various platforms; client tier on Microsoft Windows, and extended browser support	Pro-prietary	www.sas.com
Stata	Medium to high	Statistics, data mining, and academic research	Stand-alone	Microsoft Windows, Linux, and Mac OS X	Pro-prietary	www.stata.com
Weka	Medium to high	Machine learning	Programming	Microsoft Windows, Linux, and Mac OS X	Open source	www.cs.waikato.ac.nz/ml/weka

Table 1: Overview of Available Software for Statistical Analysis (Louridas & Ebert, 2013)

Watson (2011) notes that "analytics has a longer history than most people think" Over the years terminology has evolved to describe similar underlying tools and principles to decision support systems (DSS) (Watson, 2011). DSS is defined by Zwass (1998) as "an information system which is designed to support decision makers by applying decision models to large collections of data." This definition closely aligns with views of Business Analytics. While keeping a focus on Business Analytics; decades of DSS academic research to help frame our understanding of analytics. With limited prior academic research on business analytics, DSS research helps address the behavioral aspect of implementations (i.e. user interaction) with the technical features of systems.

Business analytics is evolving and research opportunities are emerging as well (Chen et al., 2012). Analytics in the beginning was all about structured data that gets cleaned and transferred into an analytics data warehouse where the data is used for statistical modeling and then presented through interactive dashboards to users. Later, BA grew into social media and unstructured data sets, where text mining and social network analysis became paramount. The latest step in the evolution of BA is mobile visualizations and analysis. Analytics went from a focus on BI technologies in 1.0 into a focus on big data, and now 3.0 focuses is embedding analytics into products and offerings (T. H. Davenport, 2013). Analytics 3.0 according to Davenport (2013):

> "Analytics 3.0 is a new resolve to apply powerful data-gathering and analysis methods not just to a company's operations but also to its offerings—to embed data smartness into the products and services customers buy."

	Key Characteristics	Gartner BI Platforms Core Capabilities	Gartner Hype Cycle
BI&A 1.0	DBMS-based, structured content • RDBMS & data warehousing • ETL & OLAP • Dashboards & scorecards • Data mining & statistical analysis	• *Ad hoc* query & search-based BI • Reporting, dashboards & scorecards • OLAP • Interactive visualization • Predictive modeling & data mining	• Column-based DBMS • In-memory DBMS • Real-time decision • Data mining workbenches
BI&A 2.0	Web-based, unstructured content • Information retrieval and extraction • Opinion mining • Question answering • Web analytics and web intelligence • Social media analytics • Social network analysis • Spatial-temporal analysis		• Information semantic services • Natural language question answering • Content & text analytics
BI&A 3.0	Mobile and sensor-based content • Location-aware analysis • Person-centered analysis • Context-relevant analysis • Mobile visualization & HCI		• Mobile BI

Table 2: Business Intelligence and Analytics Evolution
Key Characteristics and Capabilities (Chen et al., 2012)

Analytics is penetrating a lot of disciplines and its applications are becoming widespread. Researchers are promoting the use of predictive analytics in information systems research where it can help in building theories and in creating useful practical models (Shmueli & Koppius, 2011). Society for learning analytics (SOLAR) is also promoting the use of analytics in learning and training and promoting an analytics culture inside educational institutions (Siemens, 2013). Table 3 shows the different applications of BA in e-commerce, e-government, science, health, and security (Chen et al., 2012).

	E-Commerce and Market Intelligence	E-Government and Politics 2.0	Science & Technology	Smart Health and Wellbeing	Security and Public Safety
Applications	• Recommender systems • Social media monitoring and analysis • Crowd-sourcing systems • Social and virtual games	• Ubiquitous government services • Equal access and public services • Citizen engagement and participation • Political campaign and e-polling	• S&T innovation • Hypothesis testing • Knowledge discovery	• Human and plant genomics • Healthcare decision support • Patient community analysis	• Crime analysis • Computational criminology • Terrorism informatics • Open-source intelligence • Cyber security
Data	• Search and user logs • Customer transaction records • Customer-generated content	• Government information and services • Rules and regulations • Citizen feedback and comments	• S&T instruments and system-generated data • Sensor and network content	• Genomics and sequence data • Electronic health records (EHR) • Health and patient social media	• Criminal records • Crime maps • Criminal networks • News and web contents • Terrorism incident databases • Viruses, cyber attacks, and botnets
	Characteristics: Structured web-based, user-generated content, rich network information, unstructured informal customer opinions	Characteristics: Fragmented information sources and legacy systems, rich textual content, unstructured informal citizen conversations	Characteristics: High-throughput instrument-based data collection, fine-grained multiple-modality and large-scale records, S&T specific data formats	Characteristics: Disparate but highly linked content, person-specific content, HIPAA, IRB and ethics issues	Characteristics: Personal identity information, incomplete and deceptive content, rich group and network information, multilingual content
Analytics	• Association rule mining • Database segmentation and clustering • Anomaly detection • Graph mining • Social network analysis • Text and web analytics • Sentiment and affect analysis	• Information integration • Content and text analytics • Government information semantic services and ontologies • Social media monitoring and analysis • Social network analysis • Sentiment and affect analysis	• S&T based domain-specific mathematical and analytical models	• Genomics and sequence analysis and visualization • EHR association mining and clustering • Health social media monitoring and analysis • Health text analytics • Health ontologies • Patient network analysis • Adverse drug side-effect analysis • Privacy-preserving data mining	• Criminal association rule mining and clustering • Criminal network analysis • Spatial-temporal analysis and visualization • Multilingual text analytics • Sentiment and affect analysis • Cyber attacks analysis and attribution
Impacts	Long-tail marketing, targeted and personalized recommendation, increased sale and customer satisfaction	Transforming governments, empowering citizens, improving transparency, participation, and equality	S&T advances, scientific impact	Improved healthcare quality, improved long-term care, patient empowerment	Improved public safety and security

Table 3: Business Intelligence and Analytics Applications: From Big Data to Big Impact (Chen et al., 2012)

"Business Analytics Capability Model" focuses on three dimensions people, process, and technology that turn data into insights that drive business decisions (Wixom et al., 2013). Delivering value from BA technologies is a challenge that needs to be carefully managed. The market is advancing BA with progressive technologies and that is putting pressure on researchers to create research that uncover the potential of BA. The following table 4 by Chen (2012) shows a list of foundational technologies and emerging research in BA.

	(Big) Data Analytics	Text Analytics	Web Analytics	Network Analytics	Mobile Analytics
Foundational Technologies	• RDBMS • data warehousing • ETL • OLAP • BPM • data mining • clustering • regression • classification • association analysis • anomaly detection • neural networks • genetic algorithms • multivariate statistical analysis • optimization • heuristic search	• information retrieval • document representation • query processing • relevance feedback • user models • search engines • enterprise search systems	• information retrieval • computational linguistics • search engines • web crawling • web site ranking • search log analysis • recommender systems • web services • mashups	• bibliometric analysis • citation network • coauthorship network • social network theories • network metrics and topology • mathematical network models • network visualization	• web services • smartphone platforms
Emerging Research	• statistical machine learning • sequential and temporal mining • spatial mining • mining high-speed data streams and sensor data • process mining • privacy-preserving data mining • network mining • web mining • column-based DBMS • in-memory DBMS • parallel DBMS • cloud computing • Hadoop • MapReduce	• statistical NLP • information extraction • topic models • question-answering systems • opinion mining • sentiment/affect analysis • web stylometric analysis • multilingual analysis • text visualization • multimedia IR • mobile IR • Hadoop • MapReduce	• cloud services • cloud computing • social search and mining • reputation systems • social media analytics • web visualization • web-based auctions • internet monetization • social marketing • web privacy/ security	• link mining • community detection • dynamic network modeling • agent-based modeling • social influence and information diffusion models • ERGMs • virtual communities • criminal/dark networks • social/political analysis • trust and reputation	• mobile web services • mobile pervasive apps • mobile sensing apps • mobile social innovation • mobile social networking • mobile visualiza-tion/HCI • personalization and behavioral modeling • gamification • mobile advertising and marketing

Table 4: Business Intelligence and Analytics Research Framework: Foundational Technologies and Emerging Research in Analytics (Chen et al., 2012)

BA is more than “nice-to-have” and is now a requirement for competing in the marketplace (Watson, 2011). Numerous case studies on business analytics have shown it can provide benefits to organizations by enabling improvement of business processes, firm performance, and creating competitive advantage (Kohavi et al., 2002). BA systems are essential for enterprises and companies’ failing to adopt BA systems have a big gap with their competitors (Kiron et al., 2011).

In “Competing on Analytics” book, Davenport gives numerous examples of very successful companies achieving competitive advantage through BA. Harrah’s Entertainment became an industry leader with a high profile analytics in areas such as customer profitability, expected lifetime value, campaign design and development, and customer segmentations. The following tag cloud shown in figure 2 shows competitive advantage as a topic discussed heavily in BA related tags. This tag cloud was generated from a list of publications from 2000-2011, these keywords were then ranked based on their frequency, and the top 30 keywords displayed using the tag cloud visualization. More important keywords are highlighted with larger fonts as shown in figure 2 (Chen et al., 2012).

Figure 2:Tagcloud Visualization of Major Topics in the Business Intelligence and Analytics Literature (Chen et al., 2012)

In the information systems hierarchy, a DSS system is a system layer that sits on top of the transactional processing systems (TPS)(Laudon et al., 2012). TPS manages and stores transactions and provides standardized reporting which helps in making short term decisions. TPS goal is to give managers the ability to audit operational processes and provide feedback so that these operational decisions can be made faster with fewer errors. DSS systems have a different goal. DSS produce advanced analytics and predictions so that top level managers can be innovative in their thinking process and can be creative in designing strategies. Knowing this, when DSS researchers addressed performance, they used efficiency as the outcome. In practice we see the majority of analytics software industry focusing mainly on using analytics to make faster decisions. While efficiency is an important performance outcome, creativity is another important performance outcome that has largely been overlooked.

Business analytics should help organizations unlock insights (Fayyad & Uthurusamy, 2002), (Pearson, 2012). However, many companies are facing challenges in turning analytics into actionable insights and many organizations are failing in the deployment of analytics(S. E. Arnold, 2013), (Wilson, 2009). BA software vendors are successful in creating a new generation of BA systems that brings lots of capabilities and advanced algorithms to the market. Behavioral research on these new analytics technologies have not picked up in momentum yet (Montibeller & Durbach, 2013). User interaction with BA systems is a challenge and lots of research is needed (Fayyad & Uthurusamy, 2002). Research on user characteristics and the interaction with DSS was dominant in the 1980s, but it has winded down a lot after Huber (1983) criticism of the challenges to customizing DSS according to user's cognitive style. The new theories in cognitive style, the new advances in the science about intuition and brain functions, and the new advances in BA technologies put pressure on researchers to advance the behavioral studies on user interactions with DSS.

Several studies show the benefits of BA to organizations, but they fail to offer theoretical explanations of the reasons these benefits occur (Cosic et al., 2012). Extant research on decision support systems' (DSS) effectiveness produced contradicting results. Many researchers have demonstrated the positive effect DSS can have on decision quality (Sharda, Barr, & McDonnell, 1988), (Eckel, 1983), (McIntyre, 1982). At the same time, several researchers have shown that DSS use results in lower quality decisions (Coll et al., 1991), (Aldag & Power, 1986), (Goslar, Green, & Hughes, 1986), (King & Rodriguez, 1978), (Joyner & Tunstall, 1970). User interaction can provide benefits to understanding the way DSS generate benefits (Coll et al., 1991).

There are many challenges facing BA in the usability and user interaction discipline (Kriegel et al., 2007),(Fayyad & Uthurusamy, 1996). Turning BA results into actionable insights is a major challenge and users do not understand BA output or what to do with it (Kohavi et al., 2002).

IBM recognized the need to focus on integrating analytics with human cognition to generate insights. IBM next big thing after Watson is “Cognitive Systems”. According to IBM Research (http://www.research.ibm.com/cognitive-computing), Cognitive Systems are categories of technologies that uses machine learning to enable people and machines to interact more naturally to extend and magnify human expertise and cognition. Cognitive systems will extend our cognition and free us to think more creatively and speed innovation. IBM held the first Cognitive System Colloquium in October 2013.

2.2 Cognitive Fit Theory

Cognitive fit theory was introduced by Vessey (1991); the theory proposes that the correspondence between task and information representation formats leads to superior task performance for individual users. Shaft and Vessey (2006) extended the cognitive fit theory and split information representation into internal representation and external representation of the problem domain.

How information is presented and the task characteristics affect how information is processed in working memory and the decision processes used to arrive at a decision outcome (Vessey, 1991). The theory suggests that efficiency and effectiveness of the problem solution depends on a fit between the problem representation and the problem solving task. Cognitive fit occurs when the decision processes required by the task match the decision processes supported by the problem representation. When cognitive fit occurs, a consistent and accurate mental representation of the problem results. This, in turn Leads to more effective and efficient task performance. When the problem representation does not match the task, cognitive fit will not happen because similar decision processes cannot be used on both the problem representation and the task. As a result, the problem solver must exert additional cognitive load to solve the problem which will increase task time (Vessey, 1991),(Vessey & Galletta, 1991).

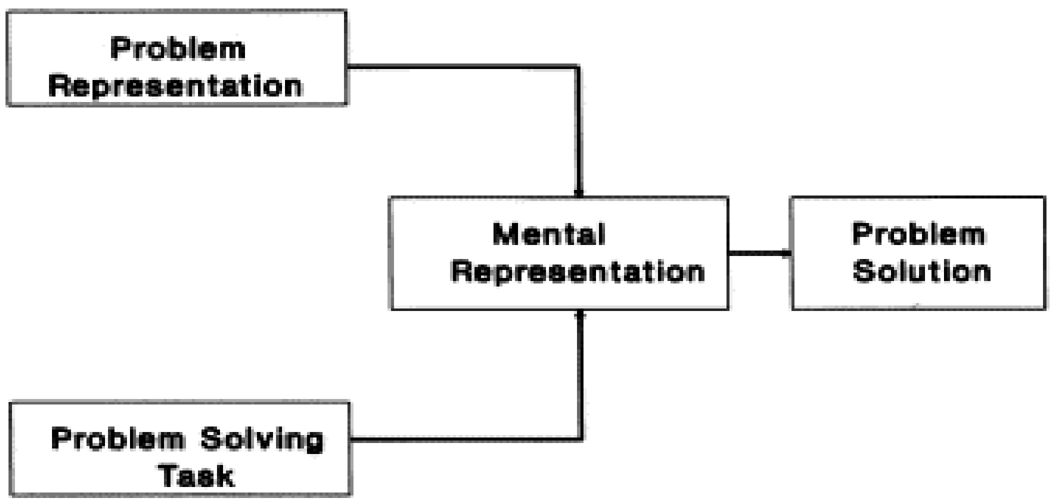


Figure 3: Cognitive Fit Model (Vessey, 1991)

According to Vessey (1991) the cognitive process of interest goes as follows: 1) when information representation, internally and externally, and task both assert similar types of knowledge, 2) this will lead the problem solver to formulate a consistent memory representation, and there will be no need for any mental representation transformation, 3) which will lead to a more effective and efficient problem-solving performance.

Internal representation is what the decision maker brings to the task based on prior knowledge and experience. External representation is the way the task is presented. Mental representation is represented in working memory and determines the decision processes and strategies used during problem solving for task solution. Problem solving performance is usually captured in terms of accuracy or effectiveness.

Graphs are spatial problem representations, since they emphasize and provide visualizations of the relationships among the data and allow the user to view the data as an integrated unit. While tables are symbolic problem representations, since they present discrete data values (Vessey, 1991),(Vessey & Galletta, 1991). External representation used in cognitive fit papers has evolved through the years from graphs vs. tables into maps and multimedia. Tasks have been extended from spatial vs. symbolic to simple vs. complicated to estimations and projections.

Upon reviewing cognitive fit literature used in the information systems discipline, you can recognize the following observations relevant to our study phenomenon. First, creativity as a dependent variable was not discussed nor tested in the literature. Most of the studies used efficiency and effectiveness to measure the outcome of cognitive fit. Second, there is not enough research on the absence of cognitive fit and how that can affect different outcomes. It might be as interesting to research different outcomes when cognitive fit does not happen. Third, external representations variable in cognitive fit theory has moved beyond the traditional graph vs. table literature and has incorporated many different kinds of representation formats. Maps, lists, and spreadsheets are some examples. Fourth, task variable has also been tested in other than spatial and symbolic types. For example, analytics vs. holistic was used, and simple vs. complex. Fifth, IS researchers have extended cognitive fit theory by adding other variables to the original model and by incorporating cognitive fit theory as the base for other theories development as in the technology dominance theory. In the following paragraphs, we will expand on the above observations in relevance to our study.

Information systems studies that used cognitive fit, measured the dependent variable in terms of efficiency in most cases. The dependent variable was measured using time and accuracy in majority of studies(Vessey & Galletta, 1991), (Dennis & Carte, 1998), (Mennecke, Crossland, & Killingsworth, 2000), (Speier, Vessey, & Valacich, 2003), (Speier, 2006), (Hock, Goswami, & Hee-Woong Kim, 2012), (Shen, Carswell, Santhanam, & Bailey, 2012). There are some IS studies that used other dependent variables. Adipat, Zhang, and Zhou (2011) used perceived ease of use and perceived usefulness as additional dependent variables. Intention to purchase and intention to return was used by (Kamis, ArnoldKoufaris,MariosStern, Tziporah, 2008). Up to our knowledge and upon a comprehensive investigation of research databases of all research papers that used cognitive fit theory– up to December of 2013 – we did not find any study which discussed or used creativity as the dependent variable or the outcome of cognitive fit variables.

The empirical research on cognitive fit used the absence of cognitive fit as the null hypothesis in the research model test, and the existence of cognitive fit as the alternative hypothesis of interest. This practice gives significant analysis and explanations of cognitive fit outcome, but does not provide sufficient analysis and explanations of the absence of cognitive fit. The null hypothesis is potentially rejected or disproved on the basis of the data that is significantly under its assumption, but the null hypothesis is never accepted or proved. Using absence of a relationship in the model allows the researcher to explore the causal mechanism that exists in the absence of this relationship and it allows researchers to find subsequent results of this relationship. Accordingly, the absence of relationship becomes the alternative hypothesis and can then be tested and proved.

This is a research gap we found while investigating cognitive fit literature, therefore, we will research and explore the absence of cognitive fit as a phenomenon by itself. Our research will study and investigate the existence of cognitive fit in the first alternative hypothesis, and will research and test the absence of cognitive fit in the second alternative hypothesis. This will permit exploration of other interesting results such as creativity.

External representations in the earlier cognitive fit literature have moved beyond the graph and table formats. Some researchers used maps (Smelcer & Carmel, 1997), (Dennis & Carte, 1998), (Mennecke et al., 2000). Other researchers have used lists vs. matrix and spreadsheets (Hong, Thong, & Kar, 2004), (Goswami, Suparna Hock Chuan Chan Hee Woong Kim, 2008). Some have also used programming languages and modeling tools as the external representations (Sinha & Vessey, 1992), (Agarwal, Sinha, & Tanniru, 1996). Although many research studies used external representations other than table and graph; none of them used business analytics outputs – decision trees or clustering for example – in earlier studies.

In a similar way task has also been extended from spatial and symbolic in Vessey's original research to many other task types. Some studies used searching vs. browsing tasks (Hong et al., 2004), others have used simple vs. complex (Speier et al., 2003), and analytics vs. holistic (Tuttle & Kershaw, 1998). Convergent vs. divergent task types are more pertinent to business analytics systems and the scenario researched in our study.

Shaft and Vessey(2006) used cognitive fit to understand software comprehension and modifications. They extended the model by distinguishing between the external and internal representations. Both representations and the interaction between them influence the mental representation for the task solution. Thus, cognitive fit depends on characteristics of internal problem representation, characteristic of the task, and presentation format.

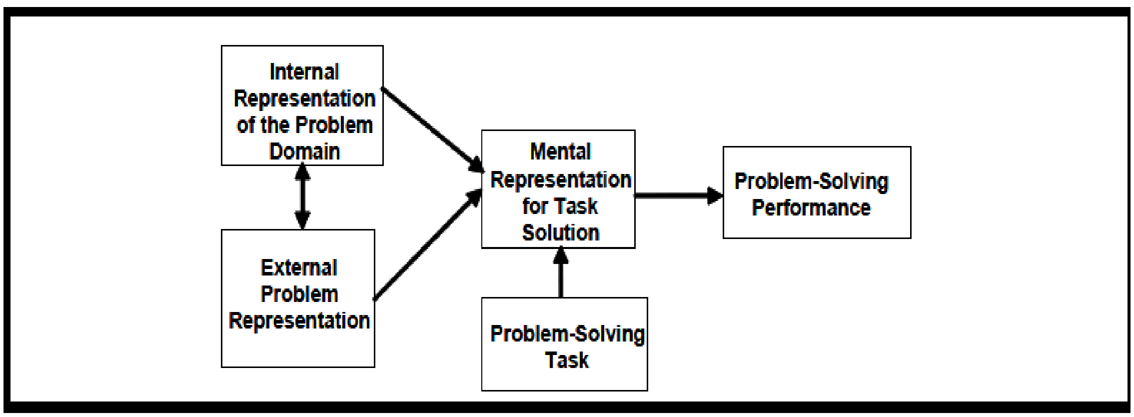


Figure 4: Extended Cognitive Fit Model (Shaft & Vessey, 2006)

Mennecke(2000) also extended cognitive fit theory to incorporate additional variables – decision maker characteristics – to the original theory variables. The study investigated how the use of spatial decision support systems influenced the accuracy and efficiency of different type of problem solvers – professional's vs. students – completing problems of varied complexities (Mennecke et al., 2000). Their study posits that individual characteristics, such as the different type of knowledge the decision maker has, should be part of cognitive fit. Subject characteristics were found to have significant effect on performance. Similarly, our study will extend cognitive fit theory by adding cognitive style variable to the original model.

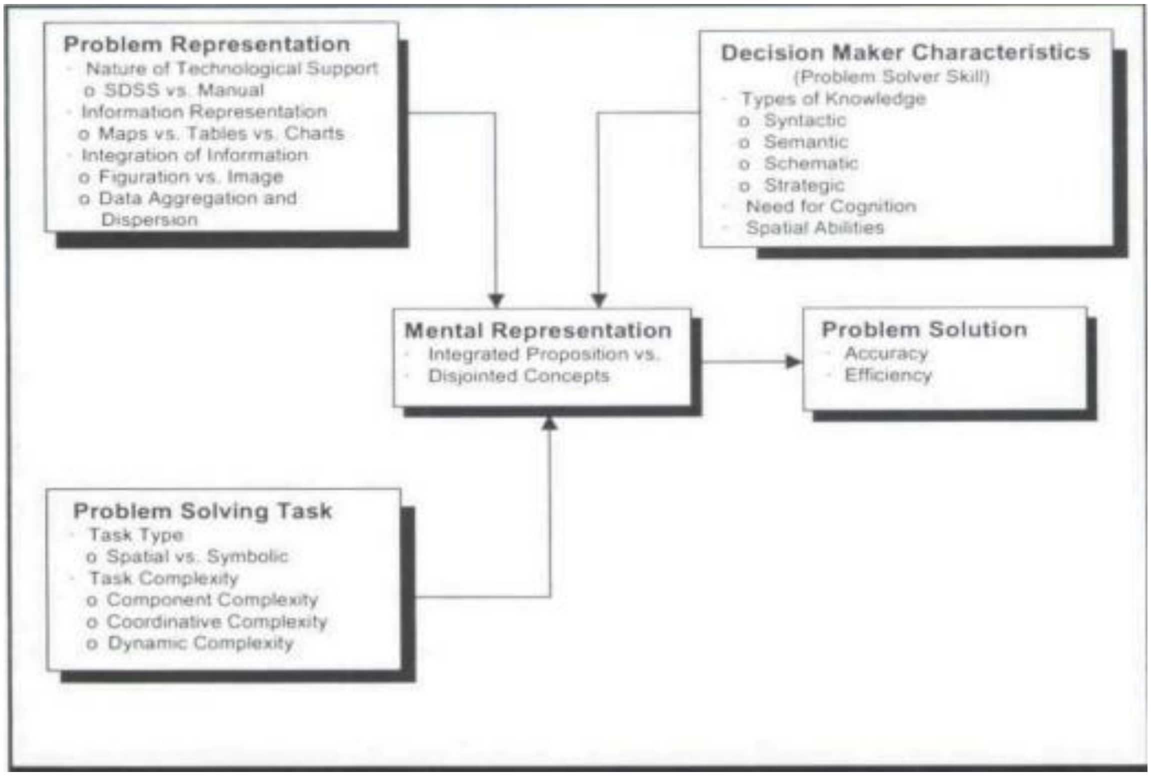


Figure 5: Extended Cognitive Fit Model (Shaft & Vessey, 2006)

Cognitive fit theory has been used in developing other theories in information systems. Arnold (1998) developed the theory of technology dominance; where cognitive fit theory was one of the base theories they used in developing this theory. Theory of technology dominance says that a decision maker may become reliant on a decision aid when decision maker’s task experience is low or when decision maker’s task experience, task complexity, decision aid familiarity, and cognitive fit are all high. One of the developed propositions of this theory says that “when task experience and perceived task complexity are high, there is a positive relationship between cognitive fit and reliance on the decision aid."

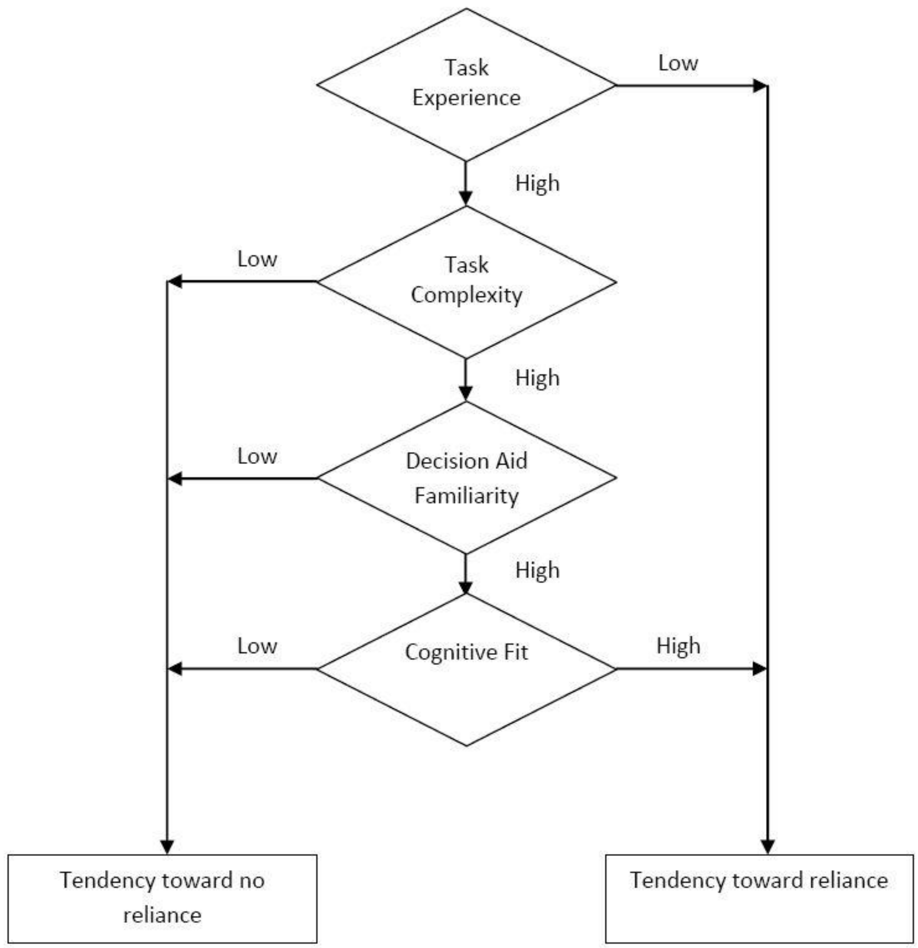


Figure 6: Theory of Technology Dominance (V. Arnold, 1998)

An interesting concept we found during the review of cognitive fit is that decision performance might be more effective when mixing presentation formats on users. Kelton, Pennington, and Tuttle (2010) reviewed cognitive fit using accounting information systems and extended cognitive fit using feedback loops to learn repeated use of the system. The authors pointed out that future research should check using a combination of external problem representations.

Cognitive fit gives a framework of the benefits for having a match between the variables which can help in digesting the problem and reaching a solution. The proposed match by this theory can enhance the time it takes to reach a solution and will require fewer resources to reach a solution. Nevertheless, cognitive fit did not measure other outcome indicators such as creativity. Cognitive fit can potentially have adverse effects on creativity since the user will depend on familiar mental models and might not pay attention to the distinctness of the situation. Integrating mindfulness theory can fill in this gap in cognitive fit theory and allow us understand causal mechanisms with the absence of cognitive fit.

2.3 Mindfulness Theory

Integrating theories will allow us to have a holistic view on the phenomenon. Using one theory to explain a phenomenon is rarely enough to present all contradictions and causal mechanisms. According to Robey and Boudreau (1999), "theories that use a logic of opposition, when coupled with appropriate research methodology, can make better sense of observed contradictions in empirical studies than theories that use deterministic logic" (Robey & Boudreau, 1999).

We will integrate cognitive fit theory with mindfulness theory as this represents an opportunity to uncover causal mechanisms working in this phenomenon. The juxtaposition of conflicting results forces researchers into a more creative, framebreaking mode of thinking than they might otherwise be able to achieve (Eisenhardt, 1989).

We wish to explore the different performance effect of user interaction with business analytics. Cognitive fit research shows performance in terms of efficiency and effectiveness, but does not show performance in terms of creativity. When we investigate creativity as a performance, the absence of cognitive fit becomes an interesting situation. The theory that can provide the causal mechanism behind cognitive fit and the absence of cognitive fit is mindfulness theory. Mindfulness research examines the phenomenon of not having an appropriate mental model for the task, and shows a degrading effect on efficiency but an enhancing effect on creativity.

Mindfulness theory is about paying attention to the information being presented in the moment, getting involved, and thinking thoroughly through the issue. Mindlessness is when the information is familiar with something that was experienced in the past, based on that the individual reaches a preconceived commitment to the conclusion (E. J. Langer & Piper, 1987).

Langer & Piper (1987) introduced mindlessness as well which posits that the repetition of routine situations would increase the chance of individuals making premature commitment to decisions. The perception of certainty introduced by familiar tasks hinders the attention of individuals to change. Individuals rely on the past and use categorizations schema to reach solutions. The advantage of mindlessness is that it improves efficiency and allows individuals to be faster in making decisions. The disadvantage of mindlessness is the premature commitment to solutions which lowers the adaptability and competence of individuals in dynamic situations.

Mindfulness happens when individuals are presented with unfamiliar situations, they get motivated to think thoughtfully through the problem. The distinct nature of the problem invokes contextual thinking of individuals which would lead to innovative solutions. Individuals get immersed in the present and can look at the distinct nature of the problem at hand. The advantage of mindfulness is that individuals are able to reach reliable creative solutions. The disadvantage of mindfulness is that it is less efficient in terms of speed in comparison with mindlessness.

According to mindfulness theory, introducing similar situations to users over and over would lead to a lower level of mindfulness which would impede creativity. Butler and Gray (2006) talked about the negative effects of cognitive fit on creativity in the information systems context.

In solving problems, people try to find orderly routines they used in the past, and apply it to the current problem; hence, people tend to ignore surrounding information (Weick, Sutcliffe, & Obstfeld, 1999). The brain evaluates the problem and will try to apply familiar historical processes. Doing this will enhance efficiency since users can solve problems with less time. Minor variations between the current problem and the historical processes will become hard to detect.

If the brain is able to make a distinction between historical processes and current problem (distinction making), the brain realizes it cannot use the same historical processes to solve the current problem. The brain will involve locally in these distinctions made and will scan the environment for more clue (environment scanning), until the brain finds a new process that can solve the problem. This newly created process is not totally new; it is based on a combination of some old processes and newly created processes.

2.4 Cognitive Experiential Self Theory

Vessey (1991) called for extending cognitive fit and for exploring other variables effect. An underlying assumption in cognitive fit is that all users will behave the same way in the fit phenomenon. Although Vessey mentioned the different thinking styles of users in her research, she did not include it in the model nor test for it, but she recommended extending cognitive fit later with more variables.

User interaction with business analytics should include three important dimensions in the study; the task, the technology, and the user. Designing successful DSS systems requires that developers pay attention to incorporating individual user characteristics (McKenney & Keen, 1974), (Davis & Olson, 1985). Adding user's cognitive style to cognitive fit will add an important element to the current phenomenon studied.

We will intersect the cognitive fit theory with the cognitive experiential self-theory (CEST) in order to measure the "internal representation" of the problem domain construct. CEST posits that individual's process information internally through two distinct information processing systems, experiential and rational. The two information processing systems are independent and operate by different rules (Epstein, 2003). Integrating this theory with cognitive fit can help in operationalizing the internal representation of the problem and it can give rigor to the analysis.

In the theoretical support of the theory, Vessey (1991) discussed two alternative information processing approaches identified in earlier literature. The first is a judgment holistic approach and the other is a choice attribute based information processing approach. The way people process information defined by Vessey and the way CEST theory defines the two alternative information processing approaches is in line.

Intuition is receiving a lot of attention in recent years. Klein(2003) explored the critical abilities of intuition and its effect on decision making. And a growing number of publications, i.e. (Hodgkinson & Clarke, 2007), studied intuition effect on organizational decision making and promoted ways to train managers on developing their intuition. An area of interest within this discipline is identifying the dominant cognitive style of managers. Allinson and Hayes (1996) developed psychometric measurement tools, cognitive style index (CSI), for identifying the dominant human cognitive style, intuitive vs. analytical.

Several measures have been developed to find the cognitive style of individuals. Some of these measures are: Myers-Briggs Type Indicator (Myers, 1962), Human Information Processing (W. M. Taggart & Torrance, 1984), and Personal Style Inventory (W. M. Taggart, Taggart-Hausladen, Taggart, & Taggart-Hausladen, 1991). The main issue with most of these measures is that they are cumbersome to be applied in organizational studies (Allinson & Hayes, 1996).

Allinson and Hayes (1996) designed the Cognitive Style Index to be used in organizational settings. While many cognitive style tools exist, we will adopt the Cognitive Style Index developed by Allinson and Hayes as our psychometric measurement tool because of its simplicity, ease of use, and application in organizational settings.

Individuals have a rather permanent stylistic orientation to the use of one hemisphere (Allinson & Hayes, 1996). Epstein (1996) assert with evidence that rational and experiential processing are independent. They posit that "behavior and conscious thought are a joint function of two systems. The systems normally engage in seamless, integrated interaction, but they sometimes conflict, experienced as a struggle between feelings and thoughts. Other evidence of the existence of two modes of processing is that people are aware of two different ways of thinking."

Hodgkinson and Clarke (2007) demonstrated the individual differences in information processing. The authors theoretically show that individuals think about decision problems and evaluate possible responses according to two processes. The first is a largely automated pre-conscious process, involving the development and deployment of heuristics and intuition. The second is a deeper, more effortful process, which entails the use of analytics. These two processes work in parallel to each other, and individuals have a preference toward one of these processes.

Cognitive style has been defined by Messick (1976) as "consistent individual differences in preferred ways of organizing and processing information and experience". Intuition and Analysis are the terms used to describe the right brain and left brain thinking. According to Allinson and Hayes (1996), "Intuition, characteristic of the right brain orientation, refers to immediate judgment based on feeling and the adoption of global perspective. Analysis, characteristic of the left brain orientation, refers to judgment based on mental reasoning and a focus on detail."

INTUITION	ANALYSIS
Non-conscious. Learners are unaware that they are acquiring and using knowledge	*Conscious* Learners are aware that they are acquiring and using knowledge
Automatic Because learning and problem solving is a non-conscious process it happens automatically and without any deliberate effort or attention.	*Intentional/deliberate* Learning involves a deliberate and conscious effort to achieve understanding.
Non-selective Intuition is non-selective because it draws on all available data and does not involve any conscious attempt to filter out any elements that appear to be irrelevant.	*Selective* Analysis is selective because it involves attending to and thoroughly assessing only those elements of a situation that are perceived to be relevant
Unconstrained Intuition is unconstrained because it includes the processing of non-salient associations between elements. These associations are so	*Constrained Rule based/rational* Analysis is constrained because it is restricted to the processing of salient associations between elements. Because

weak that they are below the threshold for conscious awareness and therefore they are inaccessible to conscious control and logical manipulation.	learners are consciously aware of these associations, the processing of information tends to be much more rational and open to conscious manipulation.
Holistic (big picture), Intuition is holistic in the sense that it focuses on the big picture and considers all elements of a situation *simultaneously.*	*Segmented (focus on parts)* Analysis is a fragmented process in the sense that it involves considering all the separate parts of a situation in turn.
Synthesis and recognition of patterns Intuition involves synthesizing data and recognizing connections that build to provide a non-conscious understanding of the rules and principles that govern a situation.	*Logical search for connections* Analysis involves a search for connections that entails a conscious step-by-step application of rules or other systematic procedures and/or the formulation and testing of hypotheses.

Table 5: Differences Between Intuition and Analysis (Allinson & Hayes, 1996)

2.5 Cognitive Style and DSS in earlier research

Several decision support systems researchers have found that individual user characteristics should play an important role in the design and development of DSS systems (McKenney & Keen, 1974), (Davis & Olson, 1985). Other researchers exerted evidence that task characteristics, structured versus unstructured, are the important factors that should influence DSS use and design (Chervany & Dickson, 1978), (Huber, 1983), (Webby & O'Connor, 1994). We examined the role of both, user characteristics and tasks, in enabling better DSS outcome through the lenses of cognitive fit theory.

Chakraborty, Hu, and Cui (2008) found that user cognitive style has a significant direct effect on technology acceptance constructs: ease of use, usefulness, and subjective norms. User cognitive style has been proven important in understanding intentions to use a technology. We are extending these studies which looked at user cognitive style effects, by looking at how cognitive style can also affect DSS outcome.

Extant research has shown that managers will not use DSS systems which do not allow them to make decisions according to their style (De Waele, 1978), (Sprague & Carlson, 1982). Whereas, Huber (1983) argued that cognitive style influence on DSS design is exaggerated. His argument was that cognitive style has not been developed well enough to be used in system design and is lacking a foundational theory to support it. And he said that systems will become very flexible in the future which can fit the different cognitive styles of users. Going forward in history, many researchers have developed several instruments that can identify the cognitive style of individuals, and cognitive-experiential self-theory of personality was developed. Additionally, research is still showing that DSS is still predominantly supporting the analytical cognitive style, but is still lagging in incorporating the intuitive cognitive style. This undermines Huber’s call for stopping research on cognitive style and DSS design (Huber, 1983).

Lu, Yu, and Lu (2001) investigated cognitive style effect on DSS acceptance. Although Lu's research is studying the same overall phenomenon as our research paper, this research paper is different in many ways. First, our research focuses on the cognitive fit theory studying the characteristics of fit and its subsequent effects. Lu looked at how cognitive style, not cognitive fit, can affect DSS intention to use. Second, we looked at how user cognitive fit affects decision quality. While Lu examined how cognitive style of users would affect their perceived ease of use and perceived usefulness of a DSS. Third, our research is using the latest business analytics models, specifically the latest data mining models, in our experiment. Lu used traditional statistical models such as fuzzy weighted-sum model, analytic hierarchy process, and linear weighted-sum model.

Epstein (2003) developed the cognitive-experiential self-theory of personality, and many researchers have developed several instruments that can identify the cognitive style of individuals. Additionally, research is still showing that DSS is still predominantly supporting the analytical cognitive style, but is still lagging in incorporating the intuitive cognitive style (Robey & Taggart, 1982), (Sauter, 1999), (Kuo, 1998). This again undermines Huber (1983) call for stopping the research on cognitive style and DSS design.

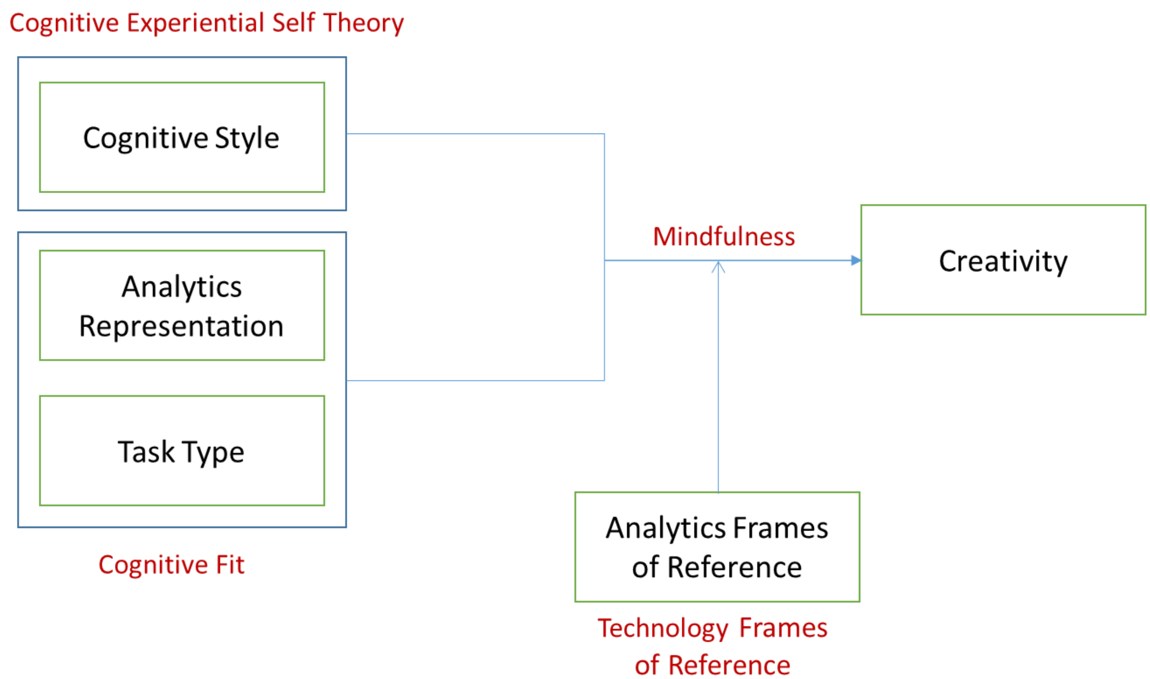


Figure 7: Conceptual Model

2.6 Technological Frames of Reference Theory

When people use business analytics, they come at it with assumptions, expectations, and knowledge about it. User's interpretations of business analytics shape their attitude towards it. "Understanding of people's interpretations of a technology is critical to understanding their interaction with it" (Orlikowski & Gash, 1994). User's perceptions of business analytics impose a cognitive structure that is used to solve the problem.

On the one hand, as Gioia (1986) [p. 346] notes, frames are helpful when they structure organizational experience, allow interpretation of ambiguous situations, reduce uncertainty in conditions of complexity and change, and provide a basis for taking action.

An individual's frame of reference has been described as "a built-up repertoire of tacit knowledge that is used to impose structure upon, and impart meaning to, otherwise ambiguous social and situational information to facilitate understanding" (Gioia, 1986)[p. 56]. "Frames are likely to be both time- and context-dependent, and are always more valid when examined in situation rather than assumed ahead of time" (Orlikowski & Gash, 1994).

Orlikowski and Gash (1994) defined technology frames as the understanding of particular technological artifacts, and they include not only knowledge about the particular technology but also local understanding of specific uses in a given setting.

Endsley (2000)said that the sources of information for Situation Awareness SA come from system knowledge, interface knowledge, and the real world. Technological frames of reference create mental model of the described situation and form a "situation model". External cues from the situation being evaluated, goals of the user, past experience with technology, expectations on the role of technology activate these situation models.

For example, some users think that computers are dumb processing machines and computer decision making is not helpful. Those are very cautious in taking any recommendation from an analytics system and they will depend on their own abilities to interpret the results and make a decision. Other users think that computers have superior abilities and can augment the gaps in human intelligence; hence they rely on the analytical system recommendation more than others.

Davidson did two research studies using technology frames of reference theory. In the first study, she investigated how technology frames of reference and shifts of these frames influence sense making during requirement determination. The study used qualitative measures to measure technology frames of reference (E. J. Davidson, 2002).In her second study; Davidson (2006) discussed the need for further development in the theoretical framework. The study calls for development by focusing analysis on frame structure, investigating framing as a dynamic interpretive process, and examining cultural and institutional basis of organizational frames (E. Davidson, 2006).

We need to integrate cognitive fit theory with technological frames of reference in order to get a complete understanding of user's interaction with business analytics. Cognitive fit theory examines context specific cognitive components of the problem that directly affect the understanding of the problem; while frames of reference examines surrounding cognitive factors that work in the background and have both facilitating and restraining effects. Cognitive fit looks at the mental model of the elements in the current situation; while technological frames of reference look at the mental model of the situation itself.

2.7 Creativity

Creativity can be defined as the ability to discern new relationships, examine subjects from new perspectives and to form new concepts from existing notions (Couger, 1995). Researchers have found that creativity can be enhanced and developed through cognitive variables, environmental variables, and personality variables. Creativity may not so much be the result of genius as being in an idea-nurturing work environment (Turban, Aronson, & Liang, 2005). In fact, it has been proven that decision support systems are tools that can potentially enhance creativity in the decision making process (Elam & Mead, March 1990), (Forgionne & Newman, 2007). "Creativity often originates from the sudden recognition of a similarity between disparate entities, experienced as a perceptual flip that changes one's interpretation of a given situation" (Ford & Gioia, 2000).

The topic of creativity is under researched in the information systems discipline (Müller-Wienbergen, Müller, Seidel, & Becker, 2011). "IS researchers have been predominantly employing a rather limited number of research designs aiming at a rather limited number of creativity related topics" (Müller-Wienbergen et al., 2011). Future research should give creativity enough focus and attention. Our study is investigating creativity which complies with calls for future research on creativity, but that adds to our challenge in break new grounds with an empirical study on creativity with advanced analytics.

Extant research investigated variables that can enhance creativity; these variables include cognitive variables (intelligence, knowledge …), environmental variables (cultural and socioeconomic factors), and personality variables (motivation, confidence …) (Forgionne & Newman, 2007). This research investigated cognitive variables (cognitive style, cognitive fit), environmental variables (technology frames of reference), and will treat personality variables (creativity traits) as control covariate variables.

"A distinction can be made between two major definitions and conceptions of creativity; creativity as a trait and creativity as an achievement" (Wierenga & Van Bruggen, 1998). Creativity as a trait is a characteristic of a person, while creativity as achievement means the creative product and the output of a process. In our study we are investigating the creativity of the output; therefore, we are theorizing creativity and adding it as a dependent variable. Creativity as a trait will be used as a control variable as stated earlier.

Most studies measure creativity as the number of ideas generated in the process of solving a problem (Wierenga & Van Bruggen, 1998).

Creativity can assist in the problem design and it can assist in identifying relevant alternatives for a problem (Forgionne & Newman, 2007). Our focus in this paper will be on creativity that can assist users in finding relevant useful alternatives for a given problem, assisting the choice phase of decision making.

DSS design features have been heavily influenced by Simon's intelligence-design-choice model of decision making. Models for creative process are very similar to the models of decision making (Elam & Mead, March 1990). The task presentation can aid users in becoming creative in finding alternatives for a given problem. Therefore, creativity enhancing DSS can be designed to provide aid to users in becoming creative in each step of the decision making process (Elam & Mead, March 1990).

"The domain specific knowledge base that an individual possesses is critical to creative performance. A higher level of relevant knowledge should facilitate higher levels of creativity" (Elam & Mead, March 1990). Therefore, domain experience will be one of the control variables we will use in this study.

Limited number of research papers investigated decision support systems impact on creativity. Forgionne and Newman (Forgionne & Newman, 2007) conducted an experiment to find empirical evidence that creativity-enhanced decision making support systems improve decision making. The study investigated in an experiment how creativity DSS enhanced the time to take a decision and the quantity of ideas generated.

Creativity enhancing decision making support systems will have the conceptual architecture shown below.

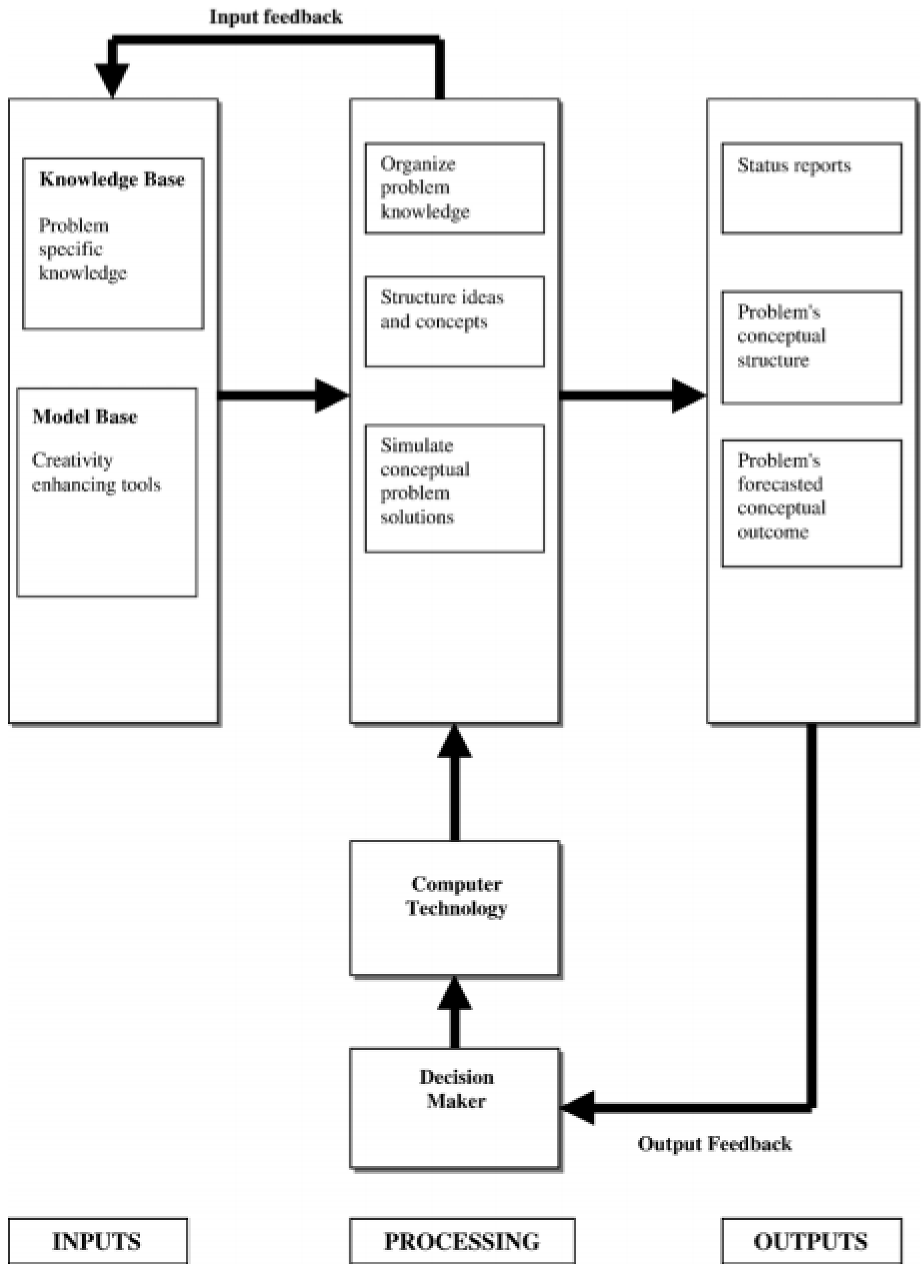


Figure 8: Creativity Enhancing Decision Making Support Systems (Forgionne & Newman, 2007)

Another empirical study that looked at the link between DSS and creativity investigated how the process and the software helped users in their decision making (Marakas & Elam, 1997). The study results found that the capability of DSS to provide directed guidance in the application of a process combined with user knowledge of the underlying process model improves creativity enhancement over use of the either the DSS or the process alone (Marakas & Elam, 1997).

CHAPTER III

RESEARCH MODEL AND HYPOTHESIS DEVELOPMENT

3.1 Variable Definitions

Creativity:

Extant research used numerous ways to measure decision quality as a dependent variable of DSS effectiveness. Keen and Morton (1978) categorized the effects of DSS on decision quality into two categories: efficiency which measure speed or reliability, and effectiveness which measure quality or accuracy. Coll (1991) posit that DSS useful outcome is measured by the degree users believe it to be.

Creativity is the dependent variable in our model. We will measure the creativity of convergent and divergent tasks by examining the number of recommendations developed by the user and the quality of these recommendations. These recommendations will be assessed by two independent raters and will score each recommendation based on general creativity quality criteria. Based on a comprehensive empirical study of creativity quality criteria used in research, the study found the following four dimensions to be comprehensive creativity quality measures: Novelty, workability, relevance, and specificity (Dean, Hender, Rodgers, & Santanen, 2006). The items used in these measures will be used to evaluate recommendations. The following provides a definition of how the four dimensions will be measured (Dean et al., 2006):

- Novelty: an idea is most novel if nobody has expressed it before.
- Workability: an idea is workable if it does not violate known constraints or if it can be easily implemented.
- Relevance: an idea is relevant if it satisfies the goals set by the problem solver.
- Specificity: an idea is thorough if it is worked out in detail.

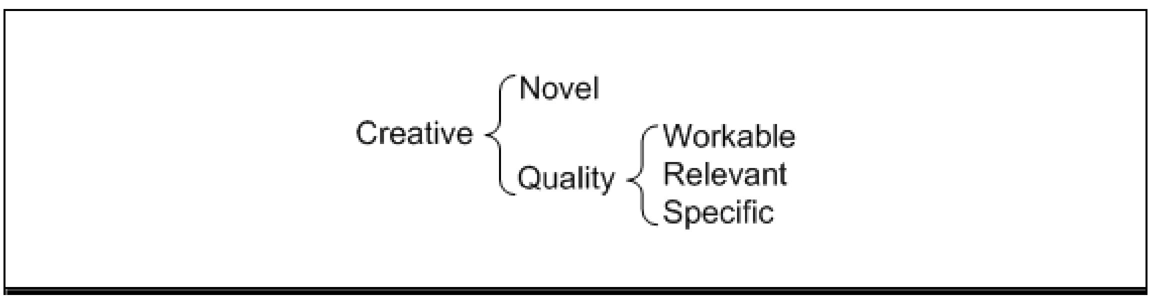


Figure 9: Relationships Among Creativity Dimensions (Dean et al., 2006)

In order for the two raters to be able to evaluate answers based on similar assumptions, we will use the creativity scales definitions developed by (Dean et al., 2006) to score the answers (shown in table 6 below).

#	Dimension	Definition
1	***Novelty****	The degree to which an idea is original and modifies a paradigm.
1.1	Originality	The degree to which the idea is not only rare but is also ingenious, imaginative, or surprising
1.2	Paradigm relatedness	The degree to which an idea is paradigm preserving (PP) or paradigm modifying (PM). PM ideas are sometimes radical or transformational.
2	***Workability (Feasibility)***	An idea is workable (feasible) if it can be easily implemented and does not violate known constraints.
2.1	Acceptability	The degree to which the idea is socially, legally, or politically acceptable.
2.2	Implementability	The degree to which the idea can be easily implemented.
3	***Relevance****	The idea applies to the stated problem and will be effective at solving the problem.
3.1	Applicability	The degree to which the idea clearly applies to the stated problem.
3.2	Effectiveness	The degree to which the idea will solve the problem.
4	***Specificity***	An idea is specific if it is clear (worked out in detail).
4.1	Implicational explicitness	The degree to which there is a clear relationship between the recommended action and the expected outcome.
4.2	Completeness	The number of independent subcomponents into which the idea can be decomposed, and the breadth of coverage with regard to who, what, where, when, why, and how.
4.3	Clarity	The degree to which the idea is clearly communicated with regard to grammar and word usage.

Table 6: Creativity construct definitions (Dean et al., 2006)

Analytics Frames of Reference:

Users with rich analytics frames of reference have a good understanding of business analytics technologies capabilities and have experience with it; they have high regards to the role of business analytics in decision making process; and they know how business analytics technology can be used in the current situation to solve the problem.

Orlikowski and Gash (1994) used three domains to characterize technology frames of reference:

1- Nature of Technology—refers to people's images of the technology and their understanding of its capabilities and functionality.
2- Technology Strategy—refers to people's views of why their organization acquired and implemented the technology. It includes their understanding of the motivation or vision behind the adoption decision and its likely value to the organization.
3- Technology in Use—refers to people's understanding of how the technology will be used on a day-to-day basis and the likely or actual conditions and consequences associated with such use.

Internal Representation:

Internal representation in memory identified in the cognitive fit model refers to the knowledge and problem solving skills of the individual. We will focus in this study on the cognitive style of the user to represent the problem solving skills of the user.

We will use the cognitive style index discussed earlier in the theoretical foundation. We will use only two cognitive styles in our experiment for the goals of simplicity and measurement, even though we acknowledge the fact that cognitive style is a range and the two styles are at two ends of a continuum.

Although "mental representation" for task solution construct is in the extended cognitive fit model, researchers typically measured the dependent variable in their models through the quality and accuracy of the solution (Kelton et al., 2010). Decision support systems performance effect is measured in terms of decision quality (Sharda et al., 1988), (Keen & Scott Morton, 1978).

External Representation (Decision Tree and Clustering):

Our second construct, “external representation” or “analytics representation” in our case, is the way we measure the external problem representation construct. External representation is measured based on a two ends of a continuum: at one end the representation is graphical and at another end the representation is symbolic. Vessey(1991) examined external problem representation – spatial versus symbolic – with graphs at one end and tables at the other end. These two problem representations conform to the information processing style of the user. According to Vessey, rational users prefer symbolic representations while intuitive users prefer spatial representations. We are extending the problem representations to match the new representations used by business analytics systems.

Decision trees or classification trees are a well-known predictive analytics model used heavily in organizations. Decision trees maps observations about an item to conclusions about the item's target value. Decision tree is a classification technique; it involves a process of attribute selection and splitting based on the most discriminate attribute, and this process is continued until each terminal node represents a different class (I. Bose & Mahapatra, 2001). It’s a way of representing the data visually which helps decision makers in classifying subjects. Each leave in the tree uses numbers to represent the chances of each class label. Therefore, decision trees fall under the symbolic representation type.

Clustering is another business analytics model used to separate objects based on how close they are based on a number of dimensions. Clustering output uses a number of graphs, each graph shows how each of the identified clusters compare to each other. Therefore, clustering falls under the spatial representation type.

There are three main reasons we chose clustering and decision tree for analytics representation in our research model. First, these two analytics algorithms representations are the two representations in line with the spatial and symbolic representations in the cognitive fit theory. Additionally, certain cognitive styles match one of those two representations but not the other. Second, clustering and decision tree represent two contrasting analytics representations. Third, decision trees and clustering output represent an analytics specific output that is different from the traditional BI output.

Clustering matches intuitive cognitive style users and divergent type of tasks. Clustering describes the population and does not have an objective, this matches the way intuitive cognitive style users think. Clustering puts subjects (i.e. customers) into buckets to show which subjects are close to each other in their behavior and which subjects are distant from others in their behavior. Clustering users are not constrained to an objective schema of the model and can think about the problem in a much more comprehensive manner allowing seemingly irrelevant information to exist. This matches the way intuitive cognitive style users think; "Intuition is non-selective because it draws on all available data and does not involve any conscious attempt to filter out any elements that appear to be irrelevant" (Allinson & Hayes, 1996). In divergent tasks, people are not limited to relevant knowledge, they would do scanning and browsing to search for potentially relevant knowledge (Müller-Wienbergen, Müller, Seidel, & Becker, 2011). Clustering is an unsupervised learning technique since it tries to find hidden patterns and structures in data and there is no reward signal to evaluate a potential solution. This distinguishes clustering from supervised learning techniques like decision tree since clustering does not result in a specific set of rules to be used in decision making, but rather leaves room for the user to use his/her evaluation and judgment (I. Bose & Mahapatra, 2001). Therefore, we posit that clustering match the judgment holistic approach that Vessey (1991) discussed in her theory development.

Clustering output is represented through graphs showing the population separated into groups. Clustering graphs will show a comparison of how each one of the clusters ranks on each of the important attributes. These clustering graphs match the spatial representation Vessey (1991) used in the theory development of cognitive fit. Decision tree output is represented through hierarchical nodes, and each node has numerical values of the target variable percentage, resembling a hierarchical table. Decision tree output matches the symbolic representation Vessey (1991) used in the theory development.

Decision tree describe the subjects based on a preconceived objective. Decision tree would rank variables based on their importance in predicting the target variable. Then it creates a split based on these variables results. Then subjects would fall into each one of these tree buckets. Decision tree only keeps information relevant to the target variable. Users can only think about the problem in terms of the stated objective of the decision tree algorithm. Rational cognitive style users use a selective process similar to the decision tree output; "Analysis is selective because it involves attending to and thoroughly assessing only those elements of a situation that are perceived to be relevant" (Allinson & Hayes, 1996). Decision tree is classified as a supervised learning technique since it is selective in its data mining. Decision tree results in a set of rules that can guide future decision making. Therefore, decision tree would match the choice and selective approach that Vessey (1991) discussed in her cognitive fit theory development.

Among all analytics algorithms, clustering and decision trees represent two ends of a continuum. First, as discussed earlier, decision trees algorithm needs a target variable to develop the output, while clustering algorithm does not use a target variable to develop the output. Second, clustering is classified as one of the descriptive analytics, since it only helps users understand their population of importance. While decision trees are classified as a predictive analytics where it attempts to predict an outcome or a propensity to respond. Third, clustering falls under unsupervised learning which tries to find patterns among unlabeled data. While decision tree falls under supervised learning which uses input to predict an outcome. A decision tree is a rules induction technique, in which a set of rules are extracted that can be used in specifying the right decision (I. Bose & Mahapatra, 2001).

Business analytics produces presentation output that is specific to business analytics and different in type from business intelligence presentation output, an example would be decision trees and clustering. Decision tress and clustering each represent a different type of analytics. Decision trees represent the predictive (behavioral forecasting) type of analytics, while clustering represent the descriptive (correlations, spatial, relationships) type of analytics. Cluster analysis is an unsupervised learning technique while decision tree is a supervised learning technique.

Task Type:

We will use convergent and divergent thinking type of tasks to represent the task type in our model since convergent/divergent types are very relevant to the creativity context of our paper. “Convergent thinking refers to the mode of human cognition that strives for the deductive generation of a single, concrete, accurate, and effective solution”(Guilford, 1967). “Divergent thinking requires imagination, provocation, unstructured syntheses, serendipitous discovery, and answers that break with conformity. This mode of cognition focuses on the synthetic generation of multiple desperate answers to a given problem” (Amabile, 1998). “The convergent process in the context of creative work differs from the usual goal of information retrieval: that is, achieving an accurate match between a query and retrieved items. When acting creatively, people do not seek “known” knowledge as they do in a well-defined search; rather, they search for something potentially relevant through a process called scanning or browsing” (Müller-Wienbergen, Müller, Seidel, & Becker, 2011). On the other hand, stimulating mental associations is the divergent process. “The sudden recognition of a similarity between disparate entities experienced as a perceptual flip that changes one’s interpretation of a given situation (Ford & Gioia, 2000).

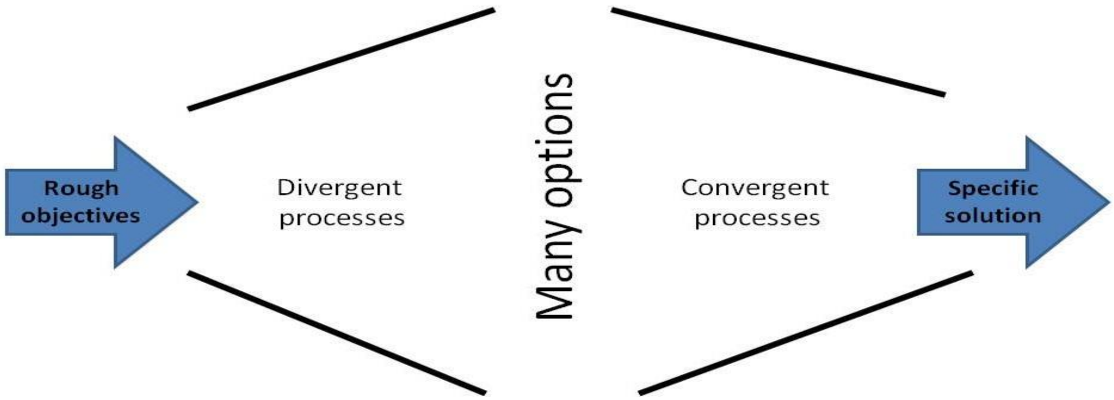


Figure 10: Divergent vs Convergent Tasks

3.2Model Development

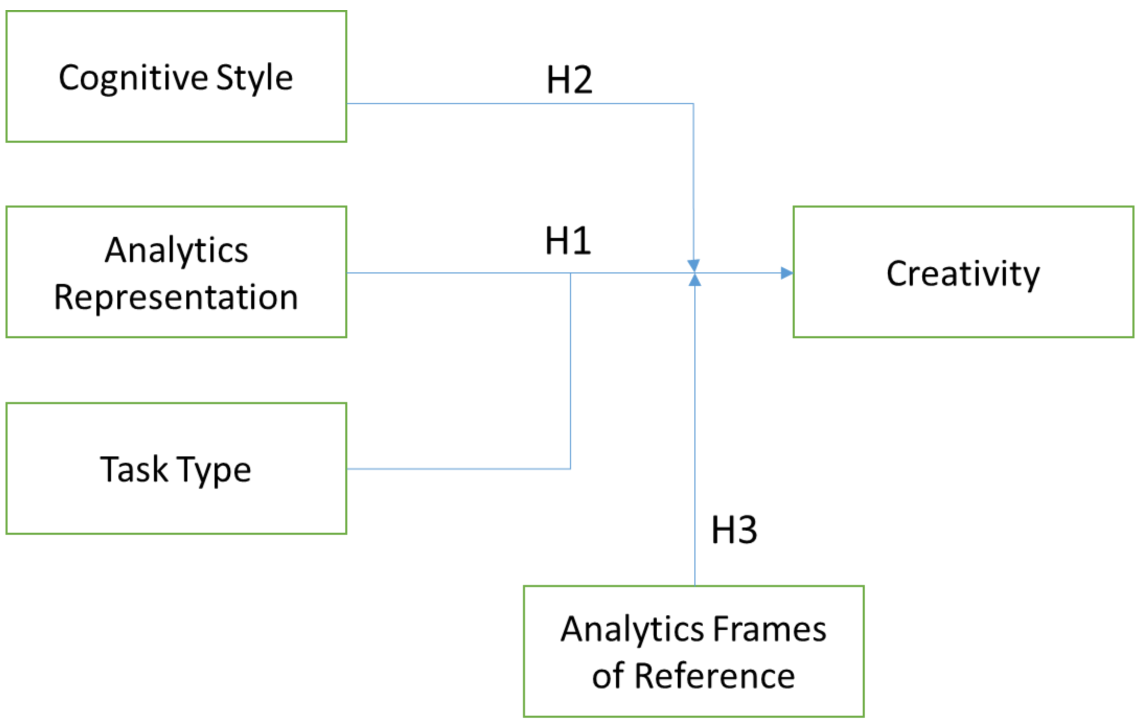


Figure 11: Research Model

People tend to ignore surrounding information once they find a fit to their problem. They find it simpler to apply historical routines and preconceived judgment to the problem in hand than to try to understand it locally (Weick et al., 1999). Finding orderly routines is good for reducing time spent on task but that might not be helpful for increasing creative decision making.

Cognitive fit theory does not address creativity; the dependent variable in cognitive fit studies is usually efficiency and performance. A rivalry theory is needed to complement the power of cognitive fit theory. Mindfulness theory can play this role. Mindfulness theory is about paying attention to the information being presented in the moment, getting involved, and thinking thoroughly through the issue. Mindlessness is when the information is familiar with something that was experienced in the past, based on that the individual reaches a preconceived commitment to the conclusion.

Vessey shows how graphical plus tabular representations gave equivalent results to the representation format which matches task type. While varying the representation format has an equivalent effect on performance, we show that it can have a positive effect on creativity. If output representation is always matched with task type, then this might lead to mindlessness where the situation becomes familiar to the user and he/she reach decisions fast but without getting involved in the problem mindfully. This can be explained by the mindfulness theory which shows how individuals can be more creative once they face unfamiliar situations. When the problem becomes a routine problem and the user becomes familiar with its components, the user will pay reduced amount of attention to the present problem and will try to rely more on established mental models. Creativity comes from outside the habitual idea generation (Müller-Wienbergen et al., 2011). While when the user is presented with an unfamiliar problem, the user will pay more attention to the context and the situated challenge. This will force the user to come up with new ways to adapt to the problem and bring new perspectives to the solution.

When cognitive fit happens, the user's ability to recognize and pay attention to cues in the problem is degraded, actually that is why users are faster in their decision making process. Creativity is degraded as well since creativity comes from the ability to identify cues in the problem: "the search for ideas in associative memory model, proposed by (Nijstad & Stroebe, 2006), this model assumes that knowledge is cue dependent".

Cognitive fit reinforces internal idea generation loop using the habitual idea generation method; therefore, reducing user's ability to recognize external stimuli which hinders creativity. "External stimuli constitute search cues that can enhance an individual's creative performance if they reflect a category of ideas outside the reinforcing internal idea generation loop" (Diehl, Munkes, & Ziegler, 2002).

Once the user breaks out of using the same perceptions and processes to reach a solution, the potential for a more creative solution is higher. "Becoming conscious of the existence of different perceptions of a given task helps scrutinizing one's personal strategy for striving for a creative solution" (Shekerjian, 1990).

Weick (1999) provides deep explanation of Mindfulness that can help us understand this causal relationship. The mind will be evaluating all processes involved in solving the problem and will try to rely on history and familiar components in solving some or all of the components of the problem processes. Small deviations are hard to detect, but if the brain recognizes the distinction, "Distinction Making" process according to Weick, then the mind starts scanning the environment in a process Weick calls “Environmental Scanning”.

Once this reliance on familiar or historical components is interrupted, there will be a void, and the brain will find that experience is not valid, the brain will then start scanning for more context and new cues in an iterative fashion, new cues and context will be evaluated against experience in an attempt to relate these processes together, until the brain finds a way in which these diverse processes interrelate. And that is creativity. Although mindfulness started when experience was not valid, it ended using some components from history and experience to find new relative combinations between current problem and experience. According to Dartnall (2007) creativity is the novel combinations of old ideas where surprise caused by a creative idea is due to the improbability of the combination. (E. J. Langer & Moldoveanu, 2000) also talked about mindfulness effect on creativity since it increases the perception of control and increases user’s attachment to the local task.

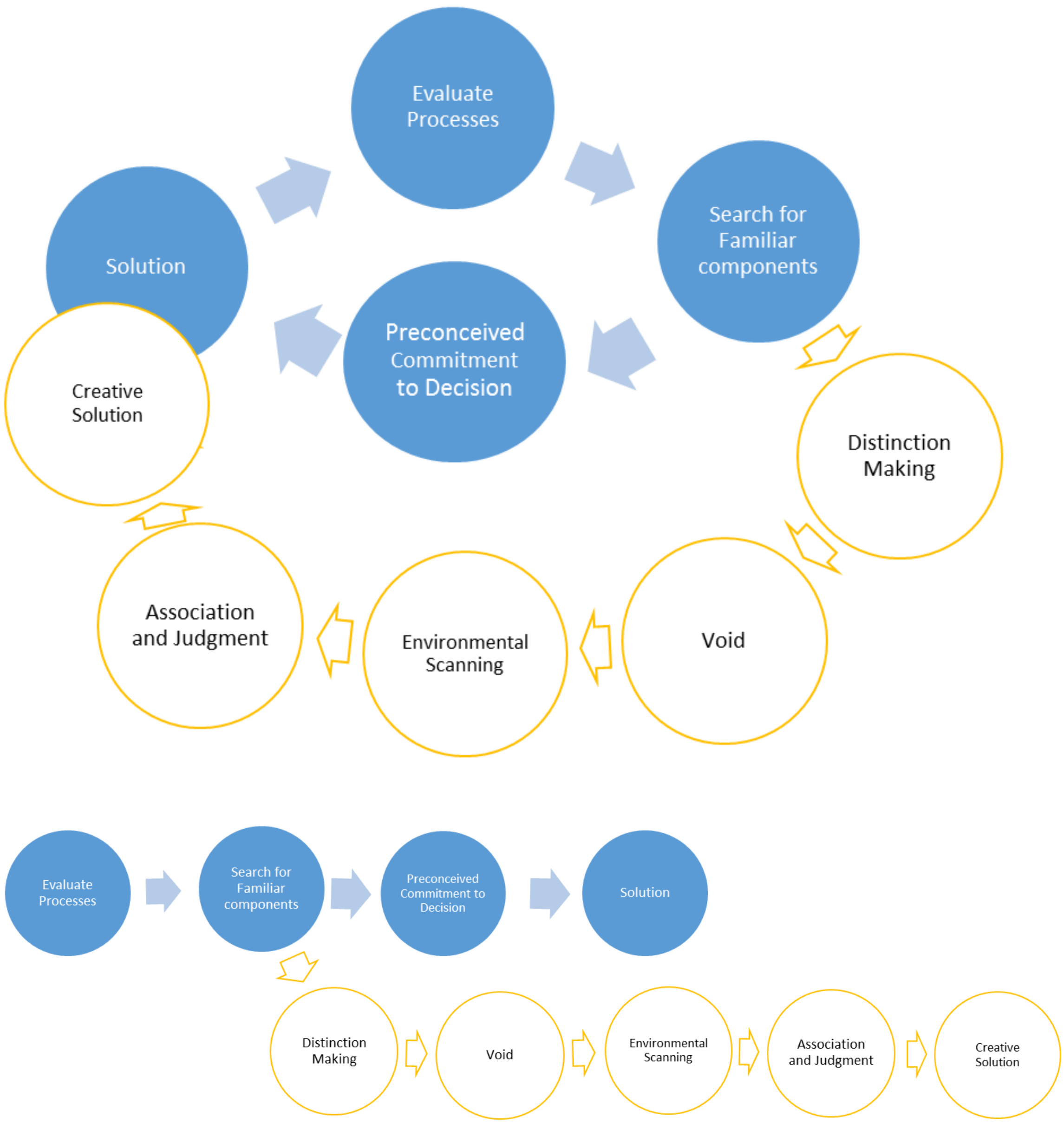


Figure 12: Mindlessness vs. Mindfulness Process

Table 7 summarizes the paradox between cognitive fit and creativity. Within cognitive fit, cognitive load is less, the brain finds previous associations and judgments made in similar situations, follows those to a preconceived commitment to a decision. In creativity, users need to defy the logic, escape the comfort zone which might lead to discomfort, in order to find new associations and judgments, this will take longer time and will affect efficiency of the user but it will positively affect the creativity of the solution.

Mindfulness	Cognitive Fit
Defying logic	Following logic
Distinction making (recognize external stimuli)	Simplify problem so its manageable (small deviations hard to detect)
Association and judgment center are activated	Association and judgment are put on auto (habitual idea generation process)
Escaping mental comfort zone	Finding mental comfort zone
Discomfort leading to new relationships (paying attention to cues)	Less cognitive load using existing relationships
Delayed judgment lead to creative decision making	Preconceived judgment and commitment to a decision
Creativity	Efficiency

Table 7: Contrasting Mindfulness with Cognitive Fit

Keeping in mind that creativity is not an outcome of divergent processes only; both convergent and divergent processes can lead to creativity. “Creative work includes both the convergent process of identifying relevant, existing things, such as factual knowledge, and the divergent process of putting these together in novel ways (Guilford, 1967), (Runco, 2007), (Weisberg, 1999).We are proposing that cognitive fit helps us understand when convergent or divergent processes can lead to creativity.

Hypothesis 1: Lack of fit between analytics representation and task type increases decision making creativity

DSS has been described by many as an aid that organizes and analyzes different factors for users (Coll et al., 1991). If one of the goals of a DSS is to organize information for users, then organizing information according to the user cognitive style would help comprehension. Additionally, Vessey (1991) posits that problem representation, which uses mental representation processes that match those required for task solution, will produce significant performance effects. Another way to consider this issue is that humans try to simplify problems to a point where they are manageable (Keen, 1981); we posit that matching business analytics task and model representation to user's cognitive style will simplify problems to users and will reduce complexity. Once the problem is understood easily, cognitive efforts will be directed toward finding the best solution rather than on spending effort on the problem itself. At that point the DSS system will help solve the problem with efficiency.

Cognitive fit did not test user's different thinking styles effect on the outcome. Although Vessey mentioned the different thinking styles of users in her research, she did not include it in the model nor test for it, but she mentioned the importance of thinking style in her study. Users are an important dimension in our study of the interaction with business analytics (McKenney & Keen, 1974), (Davis & Olson, 1985); therefore, user's internal approach in making decisions is tested.

Vessey (1991) identified and proved the first fit between holistic thinking style (intuitive cognitive style in our research), spatial representation (clustering analytics in our research), and judgment processing (divergent process in our research). The second fit was between a choice attribute style (analytical cognitive style in our research), symbolic representation (decision tree in our research) and selective information processing approach (convergent process in our research).

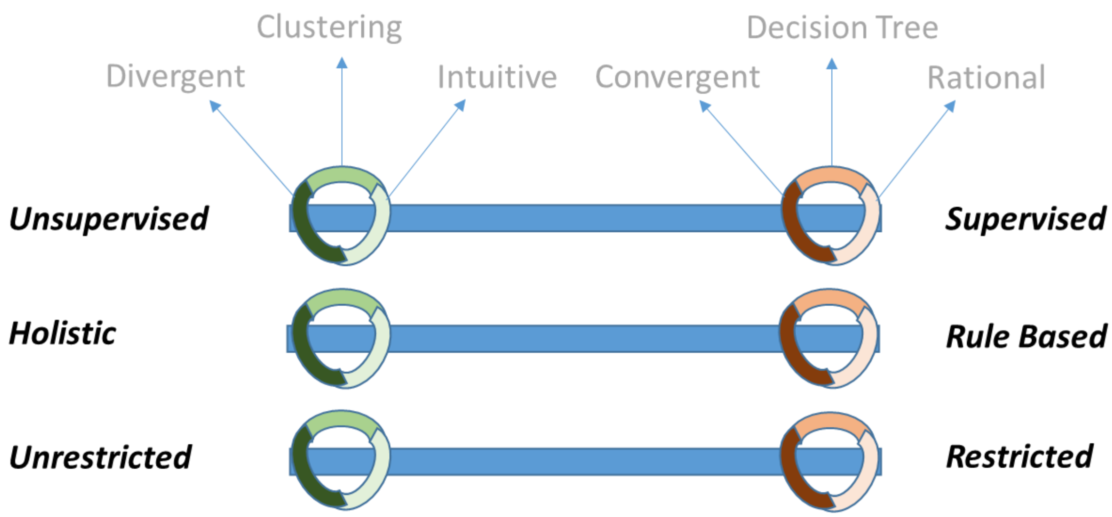


Figure 13: Components of Fit

Task type, analytics representation, and cognitive style align across three important dimensions: unsupervised, holistic, and unrestricted. In a clustering representation, there is no specific objective or target variable set in advance (unsupervised), clustering is holistic in the sense that it gives an overall overview of how data points reside based on multiple variables, and clustering incorporates all variables even the ones that are irrelevant. Divergent task and intuitive thinking style users align well with the clustering representation. On the other hand, a decision tree has a specific objective (supervised), decision tree produces rules and specific choices to a problem, and decision tree is restricted since it only includes variables that are relevant and important in predicting the outcome target variable.

Hypothesis 2: Lack of fit between analytics representation, task type, and cognitive style increases decision making creativity

Analytics frames of reference variable works in the background facilitating the effects of fit on decision making process. The effect becomes clear when we take into account the surrounding effect to the context specific effects of cognitive fit.

Orlikowski original work on the technology frames of reference showed empirical evidence of its effect on how users interact and work with systems. Users approach technology usage contexts with a set of assumptions and expectations which shape the way users interpret the problem and arrive at a solution. Therefore, analytics frames of reference will play a facilitating role in the way cognitive fit will impact creativity and efficiency. Analytics frames of reference will impose a set of assumptions and conditions on the problem being solved which will affect the actionable outcome. Understanding this social cognition around business analytics can potentially give us great explanatory power to the way users interact with business analytics.

When there is no cognitive fit, the situation becomes more challenging. Users with rich technology frames can develop inferences by using an already established cognitive process of the situation, which can make the situation less challenging to them and help drive cognitive fit. This can ultimately have adverse effects on creativity.

Hypothesis 3: Lack of fit between analytics representation, task type, cognitive style, and analytics frames of reference increases decision making creativity

CHAPTER IV

RESEARCH METHODOLOGY

We will test the proposed model by conducting an experiment. The experiment will test the different interactions between the research model antecedents (analytics representation, task type, cognitive style, and analytics frames of reference) and the dependent variables (creativity).

4.1 Experiment Survey

The experiment was conducted in a form of a survey that had four main sections. The first section asked some basic demographics questions around age, education, experience and some basic requirements for the survey around business analytics experience and decision tree and clustering experience. The second section of the survey has the cognitive style index items and the third section has the analytics frames of reference items. The last section of the survey has the two case studies. One case study used the decision tree output and two open ended questions that will be used to measure the creativity of the response, and the other case study used clustering output with two open ended questions. The two case studies were randomized, some users will get the decision tree case study first then the clustering case study, and others will get the clustering case study first then the decision tree case study. We did not want all subjects to be getting the decision tree first all the time and then the clustering case study second since this will eliminate the effect of learning from the first case study on the analysis. Subjects will go through the case study, and then will be asked to recommend solutions based on their understanding of the model and the task given. The survey is exhibited in Appendix A.

The two case studies were reviewed by four analytics managing consultants who have more than ten years of experience in analytics. Clustering and decision tree output were reviewed by experts in these tools and they provided valuable recommendations on what numbers to present, the way the output should read, and suggestions for data issues.

Qualtrics Panel consultants reviewed the survey and asked for minor changes in the survey to ensure receiving high percent of complete and valid responses. Changes were mainly forcing responses to all questions in the survey and enforcing a minimum character limit on the last four open ended questions.

Our survey followed design adequacy in the questions asked and appropriate consent and privacy measures were taken. The Institutional Review Board (IRB) for human subjects in research at Cleveland State University approved our survey. Documentation of the approval is available at Cleveland State University business school doctoral dissertation library.

4.2 Experiment Sample

Our sample represents business analytics professionals. Respondents recruited will be real world managers with at least a couple of years of experience in analytics. We used Qualtrics Panel to recruit business analytics professionals.

We received 150 responses from business analytics professionals after deploying the survey for about a month. Upon investigating responses, we found: 69 complete and valid responses; 50 responses were invalid responses because their answer to the case studies question was not meaningful; 31 responses were not complete answers.

4.3 Experiment Variables

‘Analytics Representation’ categorical variable will be tested as a fixed effect variable in the experiment since it is represented by a clustering output as the first value and decision tree output as the second value. Every subject will be exposed to both outputs, every subject will answer questions on the decision tree output and on the clustering output; therefore, this is a within subject effect.

‘Task Type’ categorical variable will be tested as a fixed effect variable. One of the open ended questions on each case study will be a convergent task and the other question will be a divergent task. Every subject will answer both convergent and divergent type tasks; therefore, this is a within subject effect.

‘Cognitive Style’ categorical variable will be tested as a fixed effect variable. Subjects will answer items that will determine if they have a dominant ‘Analyst’ cognitive style or a dominant ‘Intuitive’ style. Subjects will either have the analyst or the intuitive style, therefore, this variable is a between subject effect. We used the cutoff score that was provided to us by the authors of CSI to identify analysts from intuitive subjects.

‘Analytics Frames of Reference’ categorical variable will be tested as a fixed effect variable. This variable will take two values, low frames or high frames. Subjects will either have a low or high frames, therefore, this variable is a between subject effect. We used the median as the cutoff between low and high frames.

Variable	Experiment Design	Type of Effect	Values
Analytics Representation	Within Subjects	Fixed Effect	Decision Tree Clustering
Task Type	Within Subjects	Fixed Effect	Convergent Divergent
Cognitive Style	Between Subjects	Fixed Effect	Analyst Intuitive
Analytics Frames of Reference	Between Subjects	Fixed Effect	High Frames Low Frames

Table 8: Experiment Variables

4.4 Experiment Design

The experiment design will follow the split plot design since we have a mixed design involving two between subject variables and two within subject variables. All subjects have been exposed to decision tree and clustering, and will answer convergent and divergent type question on each analytic representation. Each subject will either have an analyst cognitive style or an intuitive cognitive style and will either have a low or high analytics frames of reference. Table 9 below show the two way fit with the original two variables that were used by Vessey in the original cognitive fit theory. The table shows the two fit scenarios that we will be comparing to the no fit scenarios.

	Convergent	Divergent
Decision Tree	Fit	No Fit
Clustering	No Fit	Fit

Table 9: Two Way Fit Experiment Cells
(Analytics Representation vs. Task)

Three-way fit is presented in table 10. There are still only two complete fit scenarios that we will be comparing to the two complete no fit scenarios. Since there are eight scenarios because of the three variables, we have four partial fit scenarios in this. We are mainly interested in fit and no fit scenarios.

		Decision Tree		Clustering	
		Convergent	Divergent	Convergent	Divergent
Subjects	Analyst	Fit	Partial Fit	Partial Fit	No Fit
	Intuitive	No Fit	Partial Fit	Partial Fit	Fit

Table 10: Three Way Fit Experiment Cells
(Cognitive Style vs. Analytics Representation vs. Task)

And table 11 has all four variables in the four way fit. There are still two complete fit scenarios and two complete no fit scenarios which we are mainly interested in.

			Decision Tree		Clustering	
			Convergent	Divergent	Convergent	Divergent
Subjects	High Frames	Analyst	Fit	Partial Fit	Partial Fit	Partial Fit
	High Frames	Intuitive	Partial Fit	Partial Fit	Partial Fit	Fit
	Low Frames	Analyst	Partial Fit	Partial Fit	Partial Fit	No Fit
	Low Frames	Intuitive	No Fit	Partial Fit	Partial Fit	Partial Fit

Table 11: Four Way Fit Experiment Cells
(Analytics Frames of Reference vs. Cognitive Style vs. Analytics Representation vs. Task)

Subject is nested within ‘Cognitive Style’, subject is crossed with ‘Analytics Representation’, subject is crossed with ‘Task Type’,’ Task Type’ is crossed with ‘Analytics Representation’, ‘Task Type’ is nested within ‘Cognitive Style’; and ‘Analytics Representation’ is nested within ‘Cognitive Style’. Subject is nested within ‘Analytics Frames of Reference’, and ‘Analytics Frames of Reference’ is nested within ‘Cognitive Style’ and within ‘Task.

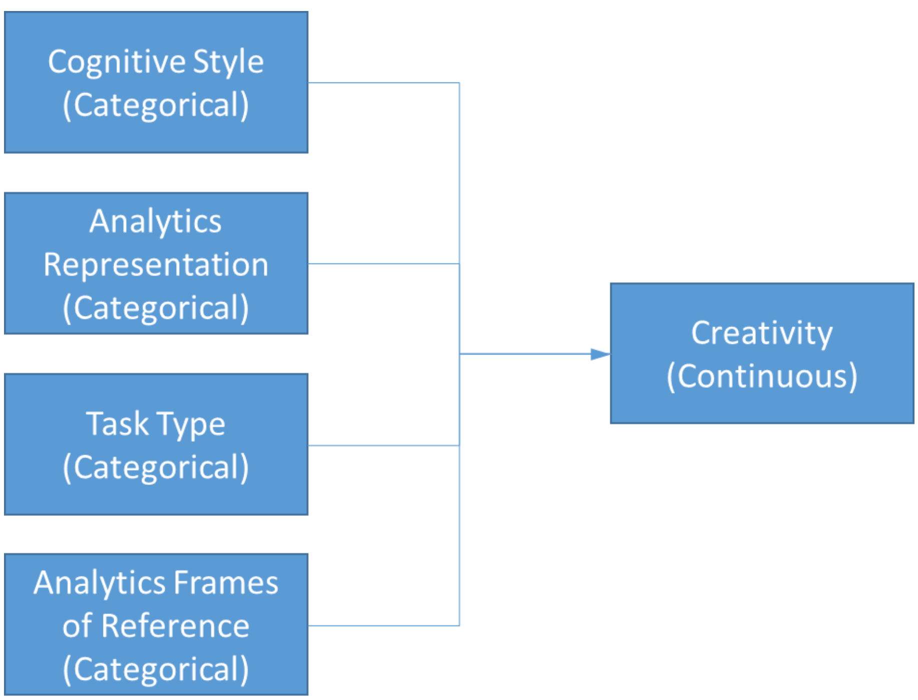


Figure 14: Experiment Test

The following table exhibits the different fit scenarios:

High Fit	High Frames	Analyst	Convergent	Decision Tree
	High Frames	Intuitive	Divergent	Clustering
Moderate Fit	Low Frames	Analyst	Convergent	Decision Tree
	Low Frames	Intuitive	Divergent	Clustering
	Low Frames	Analyst	Convergent	Clustering
	Low Frames	Analyst	Divergent	Decision Tree
	Low Frames	Intuitive	Divergent	Decision Tree
	Low Frames	Intuitive	Convergent	Clustering
	High Frames	Analyst	Convergent	Clustering
	High Frames	Analyst	Divergent	Decision Tree
	High Frames	Intuitive	Divergent	Decision Tree
	High Frames	Intuitive	Convergent	Clustering
	High Frames	Analyst	Divergent	Clustering
	High Frames	Intuitive	Convergent	Decision Tree
No Fit	Low Frames	Analyst	Divergent	Clustering
	Low Frames	Intuitive	Convergent	Decision Tree

Table 12: Fit Scenarios

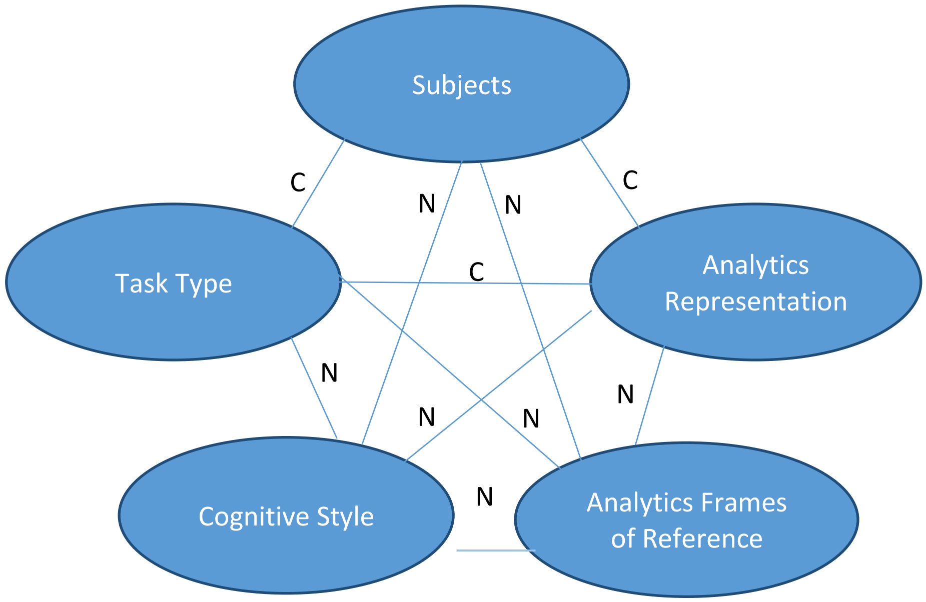


Figure 15: Experiment Design (Split Plot Design)

Preliminary Analysis

We started by looking at the demographics variables. Gender and age distributions are presented in the following two figures.

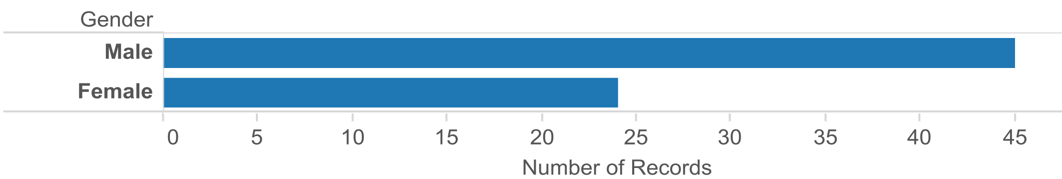


Figure 16: Gender Distribution

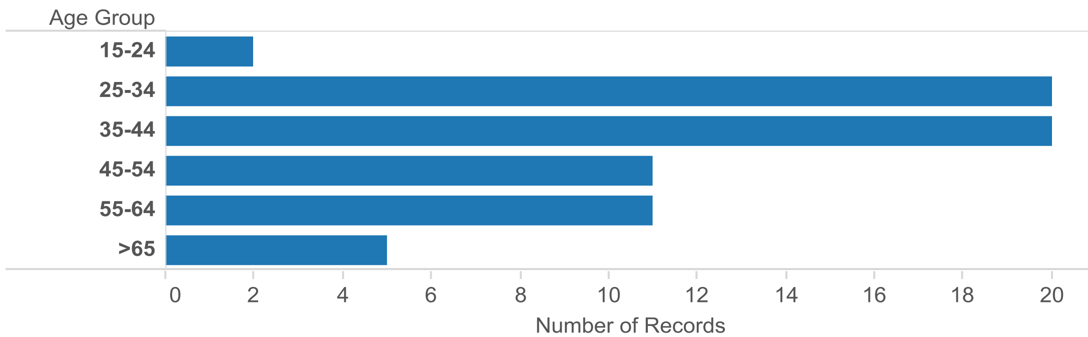


Figure 17: Age Distribution

Experience in business analytics is a prerequisite of taking the survey. Investigating the business analytics experience variable distribution shows that majority of subjects had five or more years of experience in business analytics according to figure 18 below.

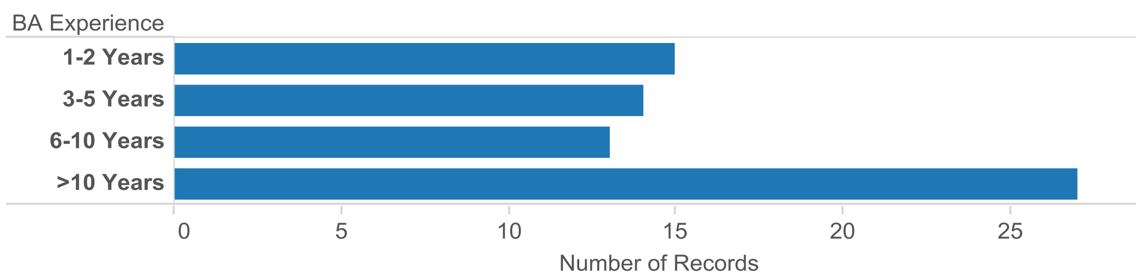


Figure 18: Business Analytics Experience

And looking at the education variable we find that the majority of subjects, 63 out of 69, had a four-year degree or higher.

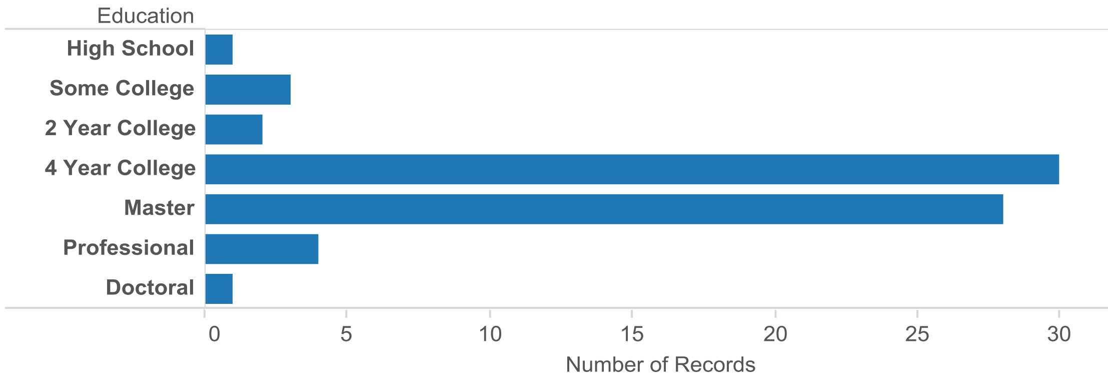


Figure 19: Education Distribution

Another prerequisite to the survey is having prior exposure to decision tree and analytics output. Reviewing subjects experience with both outputs shows that the majority had lots of experience with these outputs.

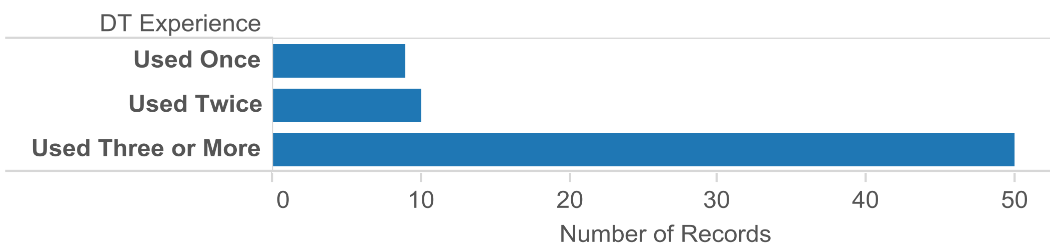


Figure 20: Decision Tree Experience Distribution

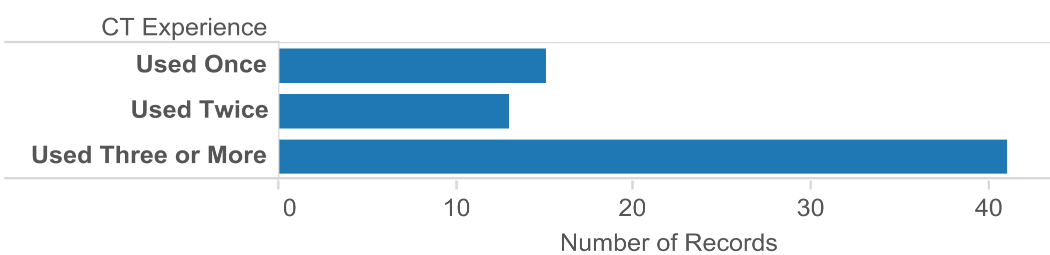


Figure 21: Clustering Experience Distribution

And figure 22 presents the distribution of analyst vs intuitive users. We used the median as the split between analysts and intuitive users since our sample represents the analytics consultant population.

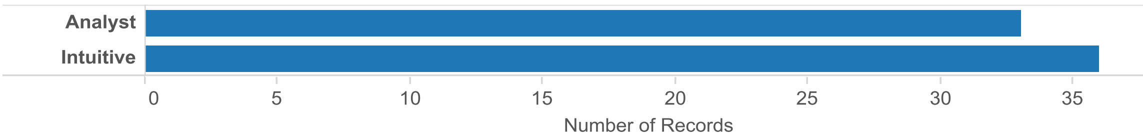


Figure 22: Cognitive Style Index Distribution

And there was a good distribution pattern for the analytics frames of references.

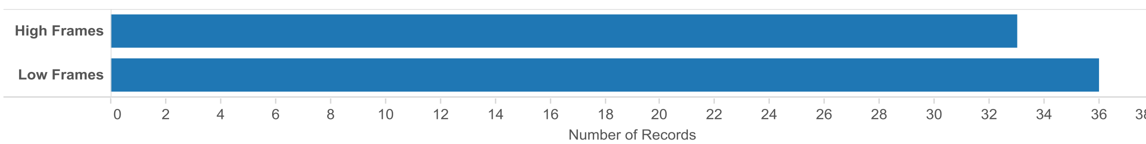


Figure 23: Analytics Frames of Reference Distribution

As a simple validation that the two anlaytics representations depict the two output styles in the original cognitive fit theory of numercial vs spatial types, and that the two cognitive styles have an effect on efficiency when there is a fit, we examined the time spent by each cognitive style on each case study when there was a fit or not fit. As noticed in the following three figures, intuitive subjects took less time with clustering output (fit) than with the decision tree output (no fit); and intuitive subjects took less time with the clustering output (fit) than the analysts (no fit). Analyst subjects took less time with the decision tree output (fit) than the clustering output (no fit); and analysts took less time with the decision tree output (fit) than the intuitive subjects did (no fit).

Thisconforms to the expectation of cognitive fit theory that says that fit has positive effects on efficiency.

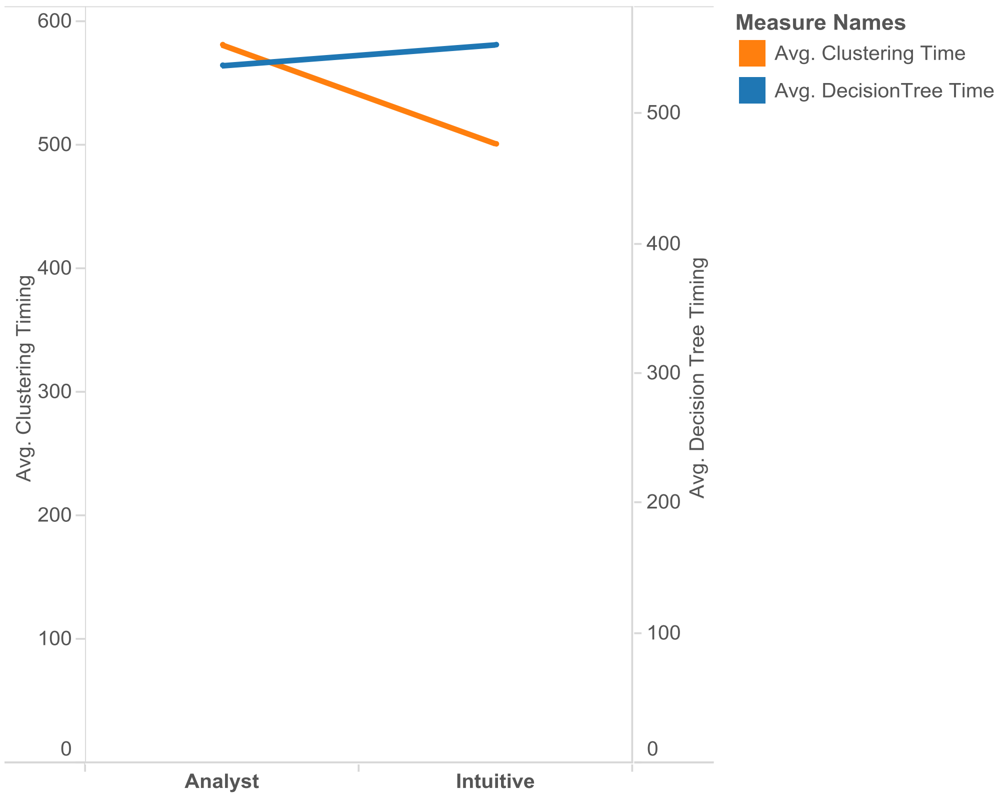


Figure 24: Average Time Spent by Each Cognitive Style on the Two Analytics Outputs

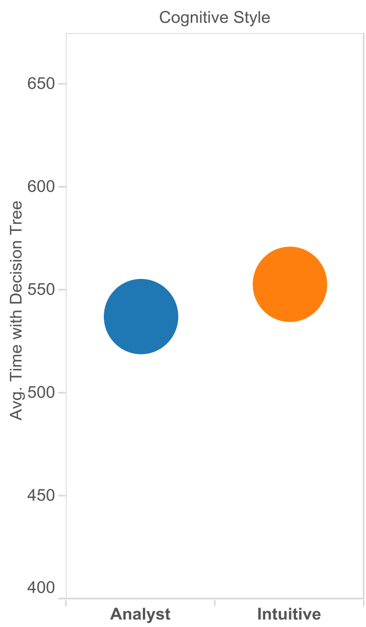


Figure 26: Average Time Spent by Each Cognitive Style using Decision Tree Output

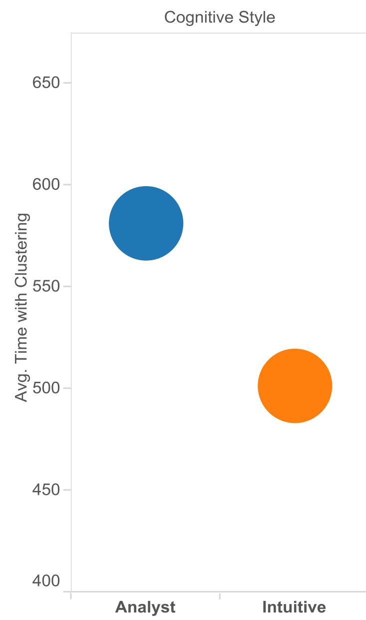


Figure 25: Average Time Spent by Each Cognitive Style using Clustering Output

4.5 Creativity Construct

To evaluate the creativity of the answers we used the following procedure:

1- We used the comprehensive creativity measure that included all consistent nine sub dimensions used by earlier researchers and developed by (Dean et al., 2006).

2- Two raters with Master level degree and experience in marketing and analysis have been trained on the nine sub dimensions.

3- Training included going through each sub dimensions definition and trying to understand it from different angles. Then we went through the examples given in the two case studies provided by the creativity measure authors (Dean et al., 2006).

4- Raters were asked to rate each sub dimension separately in each session accroding to the recommendations of (Dean et al., 2006). That way they can understand the sub dimension very well and their mind can be focused on that measure and the response rating would not be affected by their rating of another sub dimension. We also met briefly with the raters before they started rating on each sub dimension to discuss it and remove any ambiguity.

5- The two raters assigned ratings to the last four questions of the survey for all 69 responses on each of the nine creativity sub dimensions.

6- It took each rater about 60 hours to finish rating all questions across all sub dimensions. After they were done with the ratings, we had several meetings where we discussed the major discrepencies in the ratings. We would read the response, each would present their thoughts, then we made sure everyone was clear on the response and the sub dimension. Then raters in some cases had to redo the rating of the whole sub dimension after the ambiguity was cleared and they had seen where exactly they were off.

7- After that there were still some minor descrepancies between the two raters. At the most, we would find three responses with a difference of three scores between the two raters in each sub dimension. These responses were again reviewed in another session with the two raters and they had a chance to modify their rating. After about 20 hours of several meetings and discussions of the sub dimensions and the difficult responses, each rater had a chance to reevaluate their rating and adjust it.

We tested the sub-dimensions composing each factor for reliability and construct validity. First, we tested inter-rater reliability using Cronbach Alpha (Dean et al., 2006).Table 13 shows that inter-rater reliability analysis resulted in good reliability between raters on each sub-dimension.

Construct	Overall	Q17 (Decision Tree - Convergent)	Q18 (Decision Tree- Divergent)	Q14 (Clustering - Convergent)	Q15 (Clustering - Divergent)
Originality	0.83	0.85	0.83	0.84	0.84
Paradigm Relatedness	0.81	0.77	0.84	0.76	0.85
Acceptability	0.78	0.75	0.80	0.74	0.80
Implementability	0.84	0.69	0.88	0.74	0.89
Applicability	0.85	0.75	0.90	0.74	0.90
Effectiveness	0.80	0.67	0.85	0.81	0.82
Implicational Explicitness	0.86	0.89	0.89	0.82	0.83
Completeness	0.80	0.84	0.84	0.79	0.75
Clarity	0.82	0.77	0.87	0.78	0.84

Table 13: Inter-Rater Reliability on Sub-dimensions

Second, we present correlation matrices for the eight items in Table 14. We highlighted correlations between two items for each construct. Acceptability did not correlate highly with Implementability. For the remaining eight items—two for each construct—all correlations between items that measure the same construct are higher than all correlations between items that measure different constructs.

	Originality	Paradigm Relatedness	Acceptability	Implementability	Applicability	Effectiveness	Implicational Explicitness	Completeness
Paradigm Relatedness	0.6076***							
Acceptability	0.07661	0.03532						
Implementability	0.1187**	0.04428	0.23831***					
Applicability	0.30053***	0.35989***	0.22412***	0.38707***				
Effectiveness	0.29329***	0.28856***	0.21135***	0.36038***	0.53853***			
Implicational Explicitness	0.5338***	0.60459***	0.04532	0.17096**	0.44017***	0.36744***		
Completeness	0.5794***	0.60587***	0.00908	0.18532**	0.43187***	0.4109***	0.75309***	
Clarity	0.37975***	0.39944***	0.05042	0.21647***	0.32922***	0.3631***	0.53682***	0.50635***

*** p = 0.001; ** p = 0.01; * p = 0.05

Table 14: Correlations Among Sub-dimensions

We completed a confirmatory factor analysis of the model using structural equation modeling (SEM) performed using SAS. The structural model contains all the sub-dimensions; it contains the eight observed variables and four latent variables. Table 15 presents variety of fit measures to determine the appropriateness of the model.

The results indicate strong support for the integrity of the model. RMSEA (Root Mean Squared Error Approximation) fit statistic is 0.017 which is well below the 0.10 accepted level, thus this indicates good model fit(Hooper, Coughlan, & Mullen, 2008). AGFI (Adjusted Goodness of Fit) is 0.962 which is larger than 0.9, and this provides additional support that the model is a good fit. Chi square divided by degree of freedom gives 25.75 which is well above the 5.00 acceptable range (Hooper et al., 2008).

Fit Function	**Value**
Goodness of Fit Index (GFI)	0.9823
GFI Adjusted for Degrees of Freedom (AGFI)	0.9622
Chi-Square	927.94
Chi-Square DF	36
Pr > Chi-Square	< 0.0001
Probability of Close Fit	0.9109
RMSEA Estimate	0.0177
RMSEA Lower 90% Confidence Limit	0.0000
RMSEA Upper 90% Confidence Limit	0.0553

Table 15: SEM Fit Indices

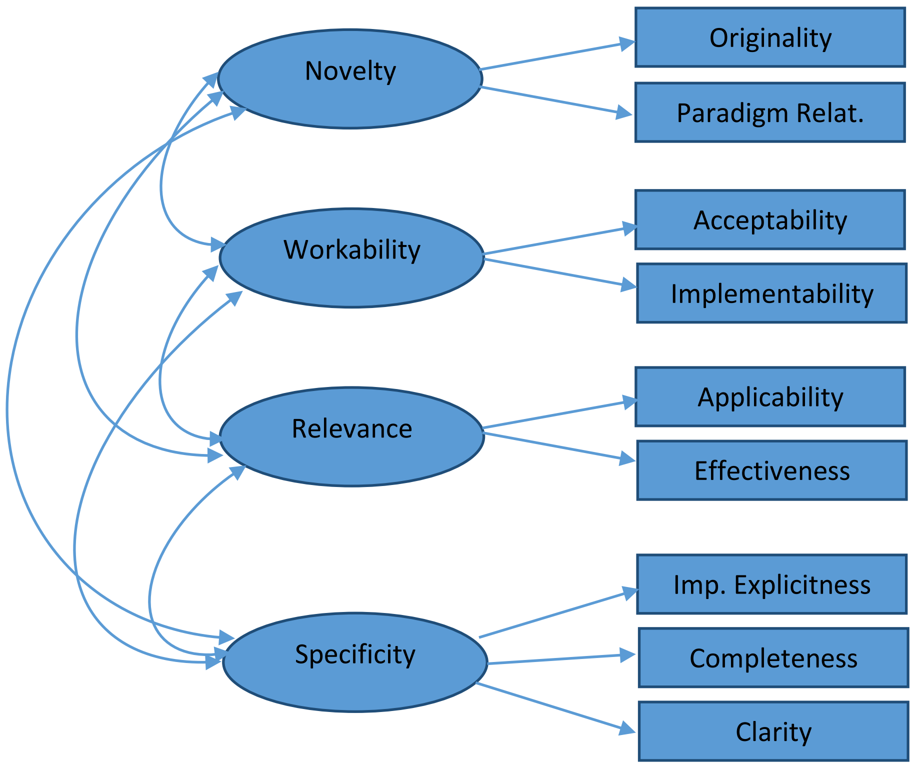


Figure 27: Creativity Construct SEM

All estimates in the linear equation of the structural equation model were significant as show in Table 16. And the covariance's among exogenous variables were all significant except for the first two variables.

Variable	Predictor	Parameter	Estimate	Standard Error	t Value	Pr > |t|
Org_Avg	F1	LV1F1	0.63455	0.04829	13.1396	<.0001
Par_Avg	F1	LV2F1	0.66729	0.04546	14.6773	<.0001
Acc_Avg	F2	LV3F2	0.25627	0.05204	4.9241	<.0001
Imp_Avg	F2	LV4F2	0.51029	0.07771	6.5666	<.0001
App_Avg	F3	LV5F3	0.62186	0.04896	12.7002	<.0001
Eff_Avg	F3	LV6F3	0.5401	0.04639	11.6436	<.0001
Comp_Avg	F4	LV7F4	0.53	0.03054	17.3552	<.0001
Exp_Avg	F4	LV8F4	0.5306	0.03103	17.0994	<.0001
Clar_Avg	F4	LV9F4	0.40692	0.03862	10.5371	<.0001

Table 16: Effects in Linear Equations

Var1	Var2	Parameter	Estimate	Standard Error	t Value	Pr > |t|
F1	F2	CF1F2	0.15163	0.10087	1.5033	0.1328
F1	F3	CF1F3	0.54366	0.06672	8.1486	<.0001
F1	F4	CF1F4	0.85492	0.03508	24.3731	<.0001
F2	F3	CF2F3	0.78913	0.1093	7.2201	<.0001
F2	F4	CF2F4	0.29499	0.09462	3.1175	0.0018
F3	F4	CF3F4	0.65982	0.05375	12.2768	<.0001

Table 17: Covariances among Exogenous Variables

4.6 Analytics Frames of Reference Construct:

Our research focus is on analytics technology; therefore, we used analytics as the technology in the frames of reference construct used in this research. We took the technology frames of reference and adopted it to analytics systems. The following are the analytics frames of reference items that were created of the definition developed by the original authors. We ran these items by the original author of the theory and she did not have any issues with them.

Analytics Frames of Reference (All Items)

a. Nature of Technology:

1- I know what business analytics represents
2- I understand well business analytics capabilities
3- I am aware of the different business analytics functionalities
4- I know nothing about business analytics
5- I know what business analytics is

6- I am aware of the nature of business analytics

7- I am not clear about what business analytics is

8- Business analytics is rich in capabilities

b. Technology Strategy:

1- I understand why organizations adopt business analytics

2- I know the value business analytics add to the organization

3- I am aware of the motivation behind adopting business analytics

4- I am skeptical of the contributions of business analytics in organizations

5- Business analytics is likely to make positive impact in organizations

6- Business analytics helps companies achieve their strategies

7- Business analytics is effective in making what organizations do better

8- Business analytics has the potential to transform the way we do business

9- Business analytics always bring positive consequences

10- Implementing business analytics will help organizations do things better

11- I believe in business analytics benefits

12- I highly value business analytics

c. Technology in Use:

1- I have used business analytics in a business project

2- I know how business analytics is used in organizations

3- I am aware of the conditions associated with business analytics use

4- I am aware of the consequences associated with business analytics use

5- It is unclear how business analytics can be useful

6- I understand how business analytics will be used to benefit organizations

7- I know how business analytics is used up to a granular level

8- I have concerns around business analytics use in companies

9- I am afraid of using business analytics in organizations

10- There is something about business analytics use that makes it inefficient

11- Business analytics is used to help support day to day operational decisions

12- Business analytics helps managerial decision making

Pre-test Technology Frames of Reference:

We used Q-sort methodology to do a pre-test and evaluate all the items created for the three dimensions of analytics frames of reference. Q-sort methodology has been used as a quality check research tool in many disciplines. The methodology is useful when researchers wish to understand and describe the variety subjective viewpoints on an issue.

We did the pre-test with six doctorate students at a northwestern university. The pre-test was successful in pointing out a couple of issues in the items we presented to them.

One of the important findings of the pre-test is that students were arguing a lot about four items. These four items were talking about the benefits and outcomes of technology use. Students struggled with these items and could not find a spot for these four questions in one of the construct dimensions, we realized that these four items were geared more toward the benefits of analytics and fall outside the boundaries of analytics frames of reference and they should be excluded from the list of items.

Most of the items mapping matched our research original mapping to the construct dimensions. There were three items that were not in concordance with the research original mapping. We changed these three items according to what the students thought they belong to.

There was one item that a student felt was a leading item (I highly value business analytics). We ended up dropping this item as well.

Here are the changes made to the above list of analytics frames of reference items. We dropped items b.4, b.9, b.11, and c.6 because they are related to analytics benefits. We dropped item b.12 because it is a leading question. We moved item a.3 to c group and moved item c.12 to b group according to student's sort order.

Then we went through an exercise to consolidate the items that are more pertinent to each dimension and ended up with the following items:

Analytics Frames of Reference (Final Items)

a. Nature of Analytics:

   1- I know what business analytics represents
   2- I understand business analytics capabilities
   3- I know nothing about business analytics
   4- I am aware of the nature of business analytics
   5- Business analytics is rich in capabilities

b. Analytics Strategy:

1- I understand why organizations adopt business analytics

2- I am aware of the motivation behind adopting business analytics

3- Business analytics helps companies achieve their strategies

4- Business analytics has the potential to transform the way we do business

5- Business analytics helps managerial decision making

c. Analytics in Use:

1- I know how business analytics is used in organizations

2- I am aware of the conditions associated with business analytics use

3- I know how business analytics is used down to a granular level

4- Business analytics is used to help support day to day operational decisions

5- I am aware of the different business analytics functionalities

To examine the scale reliability, we tested the results that came out for this construct and found that the Cronbach Alpha for these items was 0.89 which tells us that the internal consistency for these items was at a high level.

Then we ran the correlation matrices for all items in figure 26. All items that measure the same construct had higher correlations between them than the items that are measuring different construct. Only item a.3 has insignificant correlations with three items (a.2, a.4, a.5) and one significant correlation with a.1. We decided to leave item a.3 since the results of the structural equation model, that we are presenting next, shows some value in this item.

Pearson Correlation Coefficients, N = 69 Prob > |r| under H0: Rho=0															
	Tfr1	Tfr2	Tfr3	Tfr4	Tfr5	Tfr6	Tfr7	Tfr8	Tfr9	Tfr10	Tfr11	Tfr12	Tfr13	Tfr14	Tfr15
Tfr2	0.76765	1													
	<.0001														
Tfr3	-0.22598	-0.18318	1												
	0.0619	0.1319													
Tfr4	0.69107	0.71114	-0.08853	1											
	<.0001	<.0001	0.4695												
Tfr5	0.44137	0.51724	-0.10999	0.48848	1										
	0.0001	<.0001	0.3683	<.0001											
Tfr6	0.57549	0.52858	-0.40073	0.44342	0.48782	1									
	<.0001	<.0001	0.0006	0.0001	<.0001										
Tfr7	0.57549	0.49462	-0.1181	0.47298	0.3362	0.63298	1								
	<.0001	<.0001	0.3338	<.0001	0.0047	<.0001									
Tfr8	0.47078	0.48254	-0.09017	0.53549	0.71948	0.5143	0.40349	1							
	<.0001	<.0001	0.4612	<.0001	<.0001	<.0001	0.0006								
Tfr9	0.60349	0.4444	-0.23582	0.34576	0.56852	0.60929	0.52343	0.60013	1						
	<.0001	0.0001	0.0511	0.0036	<.0001	<.0001	<.0001	<.0001							
Tfr10	0.52156	0.53922	-0.26216	0.42982	0.4691	0.72972	0.63555	0.62942	0.74141	1					
	<.0001	<.0001	0.0295	0.0002	<.0001	<.0001	<.0001	<.0001	<.0001						
Tfr11	0.57467	0.63718	-0.19827	0.67285	0.39973	0.48525	0.5855	0.46934	0.42369	0.58651	1				
	<.0001	<.0001	0.1024	<.0001	0.0007	<.0001	<.0001	<.0001	0.0003	<.0001					
Tfr12	0.46396	0.57412	-0.13121	0.59229	0.29351	0.35288	0.27117	0.44779	0.265	0.39499	0.65119	1			
	<.0001	<.0001	0.2825	<.0001	0.0144	0.0029	0.0242	0.0001	0.0278	0.0008	<.0001				
Tfr13	0.47294	0.55552	-0.25354	0.4311	0.116	0.28779	0.30563	0.3589	0.18872	0.24614	0.47459	0.62974	1		
	<.0001	<.0001	0.0356	0.0002	0.3425	0.0165	0.0107	0.0025	0.1204	0.0415	<.0001	<.0001			
Tfr14	0.36661	0.46152	-0.19197	0.28001	0.08274	0.20406	0.24751	0.16329	0.18121	0.37895	0.32942	0.18858	0.37932	1	
	0.0019	<.0001	0.114	0.0198	0.4991	0.0926	0.0403	0.18	0.1362	0.0013	0.0057	0.1207	0.0013		
Tfr15	0.37182	0.49691	-0.10072	0.48674	0.11896	0.28307	0.40393	0.27764	0.11664	0.34548	0.56647	0.47575	0.60439	0.64834	1
	0.0017	<.0001	0.4103	<.0001	0.3303	0.0184	0.0006	0.0209	0.3398	0.0036	<.0001	<.0001	<.0001	<.0001	

Figure 28: Correlations Among Items

Then we ran a confirmatory factor analysis of the analytics frames of reference using structural equation modeling (SEM) using SAS. The structural model includes all three sub-dimensions and all the items. The model results are presented in table 18.

Fit Function	Value
Goodness of Fit Index (GFI)	0.7338
GFI Adjusted for Degrees of Freedom (AGFI)	0.6328
Chi-Square	225.98
Pr > Chi-Square	< 0.0001
Probability of Close Fit	< 0.0001
RMSEA Estimate	0.1533
RMSEA Lower 90% Confidence Limit	0.1289
RMSEA Upper 90% Confidence Limit	0.1779

Table 18: SEM Fit Indices for Analytics Frames of Reference

Fit indices provide support for this model. Probability of close fit (less than 0.0001), which compares the hypothesized model to the null model, is highly significant and provides strong support to this model. RMSEA estimate is at 0.15 which is higher than acceptable level but still low enough to give some support to the fit of the model(Hooper et al., 2008). Chi square divided by degrees of freedom gives a 6.25 which is above the 5.00 acceptable level (Hooper et al., 2008).

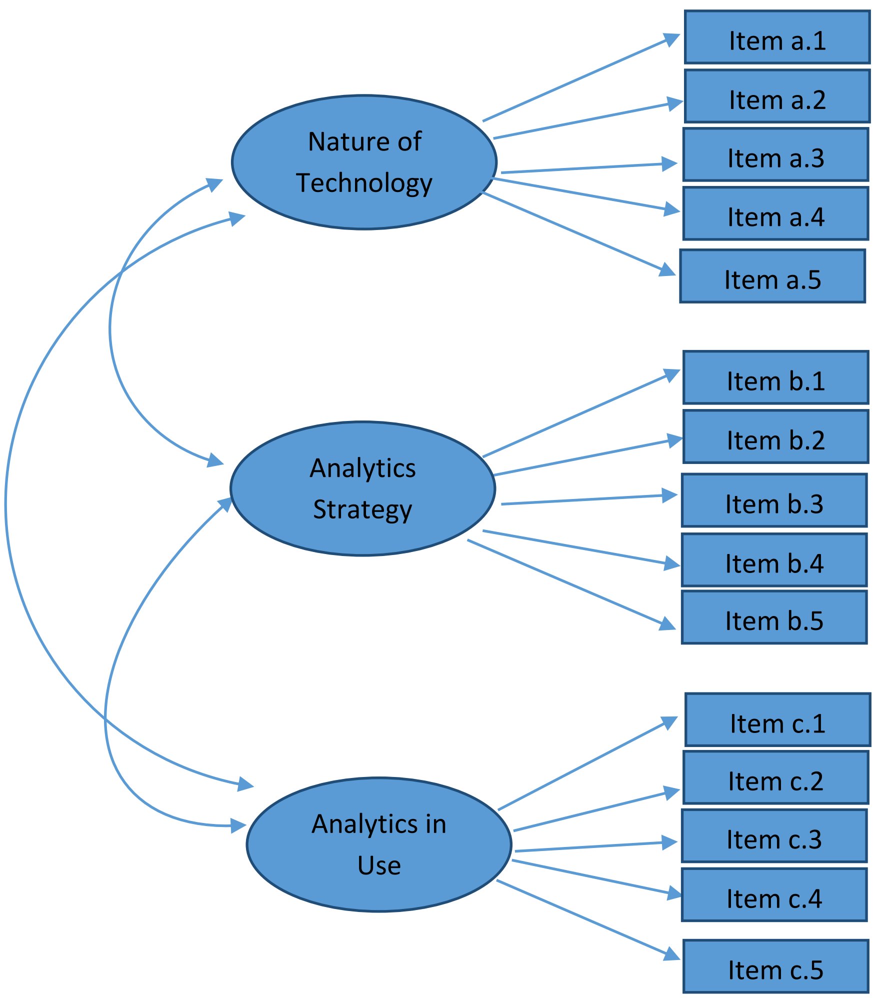


Figure 29: Analytics Frames of Reference Construct SEM

All items estimate in the linear equation of the structural equation model were significant as shown in table 19. And the covariance's among exogenous variables were all significant for the three sub-dimensions as shown in table 20.

Variable	Predictor	Parameter	Estimate	Standard Error	t Value	Pr > |t|
Tfr1	F1	LV1F1	0.57308	0.06776	8.4578	<.0001
Tfr2	F1	LV2F1	0.61244	0.06623	9.2467	<.0001
Tfr3	F1	LV3F1	-0.34068	0.18454	-1.8461	0.0649
Tfr4	F1	LV4F1	0.63406	0.0807	7.8566	<.0001
Tfr5	F1	LV5F1	0.43546	0.08828	4.9328	<.0001
Tfr6	F2	LV6F2	0.51103	0.06514	7.8456	<.0001
Tfr7	F2	LV7F2	0.45079	0.06871	6.5611	<.0001
Tfr8	F2	LV8F2	0.58393	0.09175	6.3645	<.0001
Tfr9	F2	LV9F2	0.64577	0.08414	7.6752	<.0001
Tfr10	F2	LV10F2	0.66532	0.07165	9.2862	<.0001
Tfr11	F3	LV11F3	0.56169	0.07313	7.6806	<.0001
Tfr12	F3	LV12F3	0.64327	0.09243	6.9596	<.0001
Tfr13	F3	LV13F3	0.92828	0.14412	6.4409	<.0001
Tfr14	F3	LV14F3	0.53657	0.12867	4.17	<.0001
Tfr15	F3	LV15F3	0.69178	0.10601	6.5259	<.0001

Table 19: Effects in Linear Equations for Analytics Frames of Reference

Var1	Var2	Parameter	Estimate	Standard Error	t Value	Pr > |t|
F1	**F2**	CF1F2	0.73926	0.06902	10.711	<.0001
F1	**F3**	CF1F3	0.82809	0.05823	14.222	<.0001
F2	**F3**	CF2F3	0.61525	0.09307	6.6104	<.0001

Table 20: Covariance Among Exogenous Variables for Analytics Frames of Reference

CHAPTER V

RESULTS AND DATA ANALYSIS

Our analysis investigated the effect of simple two way fit between analytics representations and task type on creativity, then the effect of three way fit between analytics representations, task type, and cognitive style on creativity, and finally the effect of four way fit between analytics representations, task type, cognitive style, and analytics frames of reference on creativity. Our hypothesis focus on fit and lack of fit conditions, therefore, our analysis will focus on fit and no fit scenarios. We will not analyze partial fit since we did not hypothesize on partial fit, although we will show some partial fit contrasts toward the end.

By examining creativity distribution, we found three responses that had very low score on all creativity dimensions and found that these responses were not valid. These three responses were outliers and we removed them from the analysis, so we ended up with sixty-six responses.

The experiment design is split plot as discussed earlier in the research methodology section. We examined this experiment design using SAS Proc Mixed procedure as suggested by the literature(Wolfinger & Chang, 1999). The mixed procedure in SAS uses maximum likelihood estimates and is recommended for three reasons. First, it computes LSMEANS which is averaged across repeated measures and whose standard error reflects the appropriate covariance structure (Yarandi, 2011). Second, we have unequal sample size between analysts and intuitive cognitive style subject, and mixed procedure is the appropriate model. Third, it allows variety of within variable covariance structure. Fourth, we can use continuous variables in the within-subject effects (Yarandi, 2011).

We will accept 10% alpha level error rate as we have a limited sample size and the experiment design has multiple variables (Cohen, 1988).

5.1 Cognitive Fit Model

Our first test of hypothesis one is intended to validate the theoretical foundation of this research, which is based on cognitive fit with creativity as a dependent variable. We ran the two-way interaction model to test the original form of fit theory (task and analytics representation) and its effect on creativity. In this basic model, we used creativity as a dependent variable and a variable representing the two way fit as independent variable in a repeated measure mixed model.

The model was statistically significant and the fit variable has a p value of 0.0735 which is statistically significant. Table 21 and 22 below show the results of this model. AIC for this model is 1,429.

Hypothesis 1: Lack of fit between analytics representation and task type increases decision making creativity

Fixed Effects	Two Way Fit	Estimate	Standard Error	P Value
Two Way Fit	Fit	-0.7996	0.4399	0.0735
Two Way Fit	No Fit			

Table 21: Fixed Effects of Two Way Fit Model

Least Squares Means	Two Way Fit	Estimate	Standard Error	P Value
Two Way Fit	Fit	24.0489	0.3104	<.0001
Two Way Fit	No Fit	24.8485	0.3116	<.0001

Table 22: Least Squares Means of Two Way Fit Model

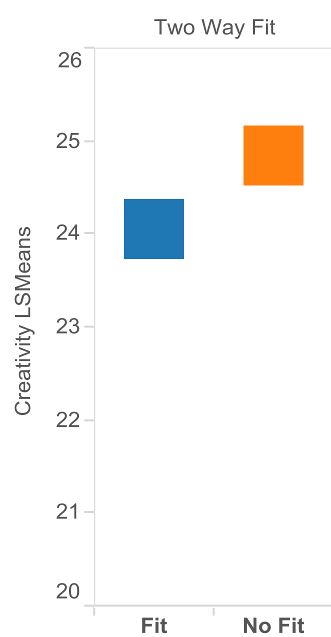


Figure 30: Creativity Least Squares Means Estimates for Two Way Fit Models

Lack of fit has higher creativity estimate than fit as shown in figure 28. When we look at the least squares means difference we find that the results are significant and in the right direction. These results provide strong support to our first hypothesis.

We checked the same model after splitting fit variable into two separate variables (task and analytics representation) and we got the same statistical significance and the same results.

5.2 Full Model

To test hypothesis two and three, we ran a full model for all our research variables of interest. This model included all direct effects and interaction effects.

Direct Effects:

Task, Analytics Representation, Cognitive Style, Analytics Frames of Reference

Interactions:

Task * Analytics Representation

Task * Analytics Representation * Cognitive Style

Task * Analytics Representation * Analytics Frames of Reference

Task * Analytics Representation * Cognitive Style * Analytics Frames of Reference

This model has an AIC of 1,390 which is smaller than the earlier model and therefore better. We notice that the interaction (Task * Analytics Representation) has a p value of 0.012 which is also better than the earlier model. This provides additional support for our H1. Three-way interaction (Task * Analytics Representation * Cognitive Style) is not statistically significant which means our H2 is not supported. Three-way interaction

(Task * Analytics Representation * Analytics Frames of Reference) is statistically significant with a p value of 0.084 which provides support to H3. Four-way interaction (Task * Analytics Representation * Cognitive Style * Analytics Frames of Reference) was not statistically significant.

Hypothesis 2: Lack of fit between analytics representation, task type, and cognitive style increases decision making creativity

Hypothesis 3: Lack of fit between analytics representation, task type, cognitive style, and analytics frames of reference increases decision making creativity

Fixed Effects	Variable	Estimate	Standard Error	P Value
Task	Convergent	-1.9289	1.0720	0.0765
Analytics Representation	Clustering	-2.7115	1.0720	0.0138
Cognitive Style	Analyst	-1.0303	1.2900	0.4274
Analytics Frames of Reference	High Frames	-3.0636	1.3720	0.0288

Table 23: Fixed Effects Model Results

Interactions	P Value
Task * Analytics Representation	0.0126
Task * Analytics Representation * Cognitive Style	0.6237
Task * Analytics Representation * Analytics Frames of Reference	0.4451
Task * Analytics Representation * Cognitive Style * Analytics Frames of Reference	0.3108

Table 24: Interaction Effects of Full Model

5.3 Post Hoc Analysis

Then we ran post hoc analysis to investigate if there were any specific scenarios that were statistically significant. Upon examining the LSMeans for the interaction effects, we listed the differences that are significant close to the 10% alpha level.

Post hoc analysis results provide enough support for our hypothesis. In all types of interactions and in lots of scenarios, whenever there is a lack of fit, even partially, creativity estimate was higher than the existence of fit.

For two-way interaction in the full model, we found that no fit (convergent with clustering) has higher creativity mean than fit (convergent with decision tree) as shown in table 25. This gives additional support to H1.

LSMeans for three-way interaction differences show support to H2 and H3. Table 24 shows that the first set fit (Intuitive, Clustering, Divergent) has lower creativity estimate than partial fit (Intuitive, Clustering, Convergent) and fit (Intuitive, Clustering, Divergent) has lower creativity estimate than no fit (Analyst, Clustering, Divergent), which gives some support to H2. And four way interactions with low analytics frames of reference has higher creativity estimate than high analytics frames of reference. For example, the last difference in table 25 shows that (Intuitive, Decision Tree, Divergent, High Frames) has lower creativity estimate than (Intuitive, Decision Tree, Divergent, Low Frames) which gives some support to H3.

Effect	Task	Analytic Representation	Cognitive Style	TFR	Task	Analytic Representation	Cognitive Style	TFR	Estimate	Standard Error	t Value	Pr > |t|	Hypothesis Supported
Two Way Fit	Convergent	Clustering			Convergent	Decision Tree			1.1055	0.7196	1.54	0.066	H1
Three Way Fit	Convergent	Clustering	Intuitive		Convergent	Decision Tree	Analyst		1.8131	1.0176	1.78	0.041	H2
Three Way Fit	Convergent	Clustering		High Frames	Convergent	Decision Tree		Low Frames	1.525	1.0176	1.5	0.070	H2
Three Way Fit	Convergent	Clustering		High Frames	Divergent	Clustering		Low Frames	1.47	1.0276	1.43	0.080	H2
Three Way Fit	Convergent	Decision Tree		High Frames	Divergent	Decision Tree		Low Frames	-1.4705	1.0282	-1.43	0.080	H3
Three Way Fit	Convergent	Decision Tree		Low Frames	Divergent	Decision Tree		Low Frames	-1.6251	0.8684	-1.87	0.034	H3
Three Way Fit	Divergent	Clustering		Low Frames	Divergent	Decision Tree		Low Frames	-1.5702	0.8801	-1.78	0.040	H3
Three Way Fit	Divergent	Decision Tree		High Frames	Divergent	Decision Tree		Low Frames	-2.0406	1.0872	-1.88	0.033	H3
Four Way Fit	Convergent	Clustering	Analyst	Low Frames	Divergent	Decision Tree	Intuitive	Low Frames	-1.574	1.2302	-1.28	0.103	H3
Four Way Fit	Convergent	Clustering	Intuitive	High Frames	Convergent	Decision Tree	Analyst	High Frames	2.2222	1.6363	1.36	0.090	H3
Four Way Fit	Convergent	Clustering	Intuitive	High Frames	Convergent	Decision Tree	Analyst	Low Frames	2.3158	1.6978	1.36	0.089	H3
Four Way Fit	Convergent	Clustering	Intuitive	High Frames	Divergent	Clustering	Intuitive	Low Frames	2.5	1.7216	1.45	0.077	H3
Four Way Fit	Convergent	Clustering	Intuitive	High Frames	Divergent	Decision Tree	Intuitive	High Frames	3.3	2.1953	1.5	0.070	H3
Four Way Fit	Convergent	Clustering	Intuitive	Low Frames	Divergent	Clustering	Intuitive	Low Frames	1.5882	1.2435	1.28	0.104	H3
Four Way Fit	Convergent	Clustering	Intuitive	Low Frames	Divergent	Decision Tree	Intuitive	High Frames	2.3882	1.8444	1.29	0.101	H3
Four Way Fit	Convergent	Decision Tree	Analyst	High Frames	Divergent	Decision Tree	Intuitive	Low Frames	-2.191	1.1438	-1.92	0.031	H3
Four Way Fit	Convergent	Decision Tree	Analyst	Low Frames	Divergent	Decision Tree	Intuitive	Low Frames	-2.2845	1.2302	-1.86	0.035	H3
Four Way Fit	Divergent	Clustering	Intuitive	Low Frames	Divergent	Decision Tree	Analyst	Low Frames	-1.5833	1.2261	-1.29	0.101	H3
Four Way Fit	Divergent	Clustering	Intuitive	Low Frames	Divergent	Decision Tree	Intuitive	Low Frames	-2.4687	1.2628	-1.95	0.028	H3
Four Way Fit	Divergent	Decision Tree	Analyst	Low Frames	Divergent	Decision Tree	Intuitive	High Frames	2.3833	1.8328	1.3	0.100	H3
Four Way Fit	Divergent	Decision Tree	Intuitive	High Frames	Divergent	Decision Tree	Intuitive	Low Frames	-3.2688	1.8575	-1.76	0.042	H3

Table 25: Significant Differences in Least Squares Means for Creativity

The graphical presentation of creativity LSMeans estimate from the model shows support to H1. Figure 31 shows that no fit (Clustering, Convergent) has higher creativity estimate than fit (Clustering, Divergent) and that no fit (Decision Tree, Divergent) has higher creativity estimate than fit (Decision Tree, Convergent).

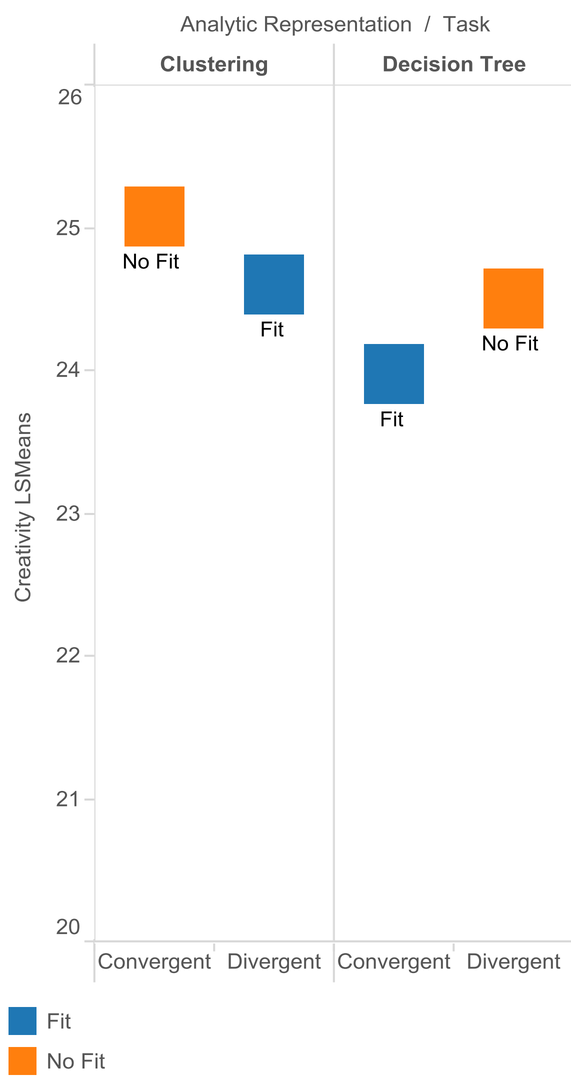


Figure 31: Creativity LSMeans for Two Way Fit

The plot of three variables: analytic frames of reference, task, and analytics representation in figure 32 shows that the relationship between creativity and fit still holds for both low and high frames of reference, but we notice that for low frames of reference there is larger difference between decision tree, divergent and decision tree, convergent than with high frames of reference.

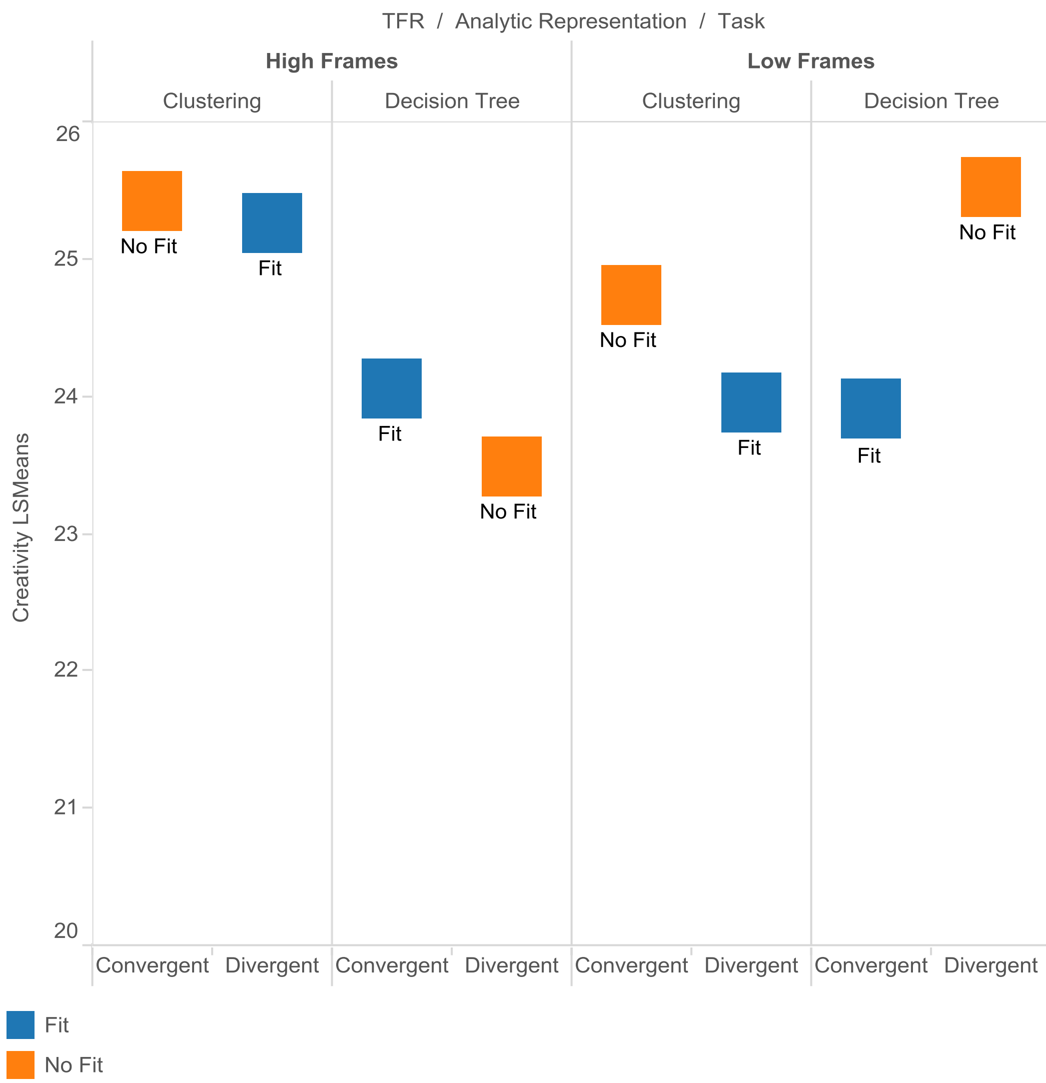


Figure 32: Creativity LSMeans for Two Way Fit with Analytics Frames of Reference

The plot of three variables: cognitive style, analytics representation, and task in figure 33 show that the fit as in analyst, decision tree, convergent has the lowest creativity estimate while the no fit as in analyst, clustering, divergent has the highest creativity estimate which support H3. But this is not true for the second set of fit. Intuitive, clustering, divergent has the lowest creativity estimate while intuitive, decision tree, convergent is not the highest as we expected in H2.

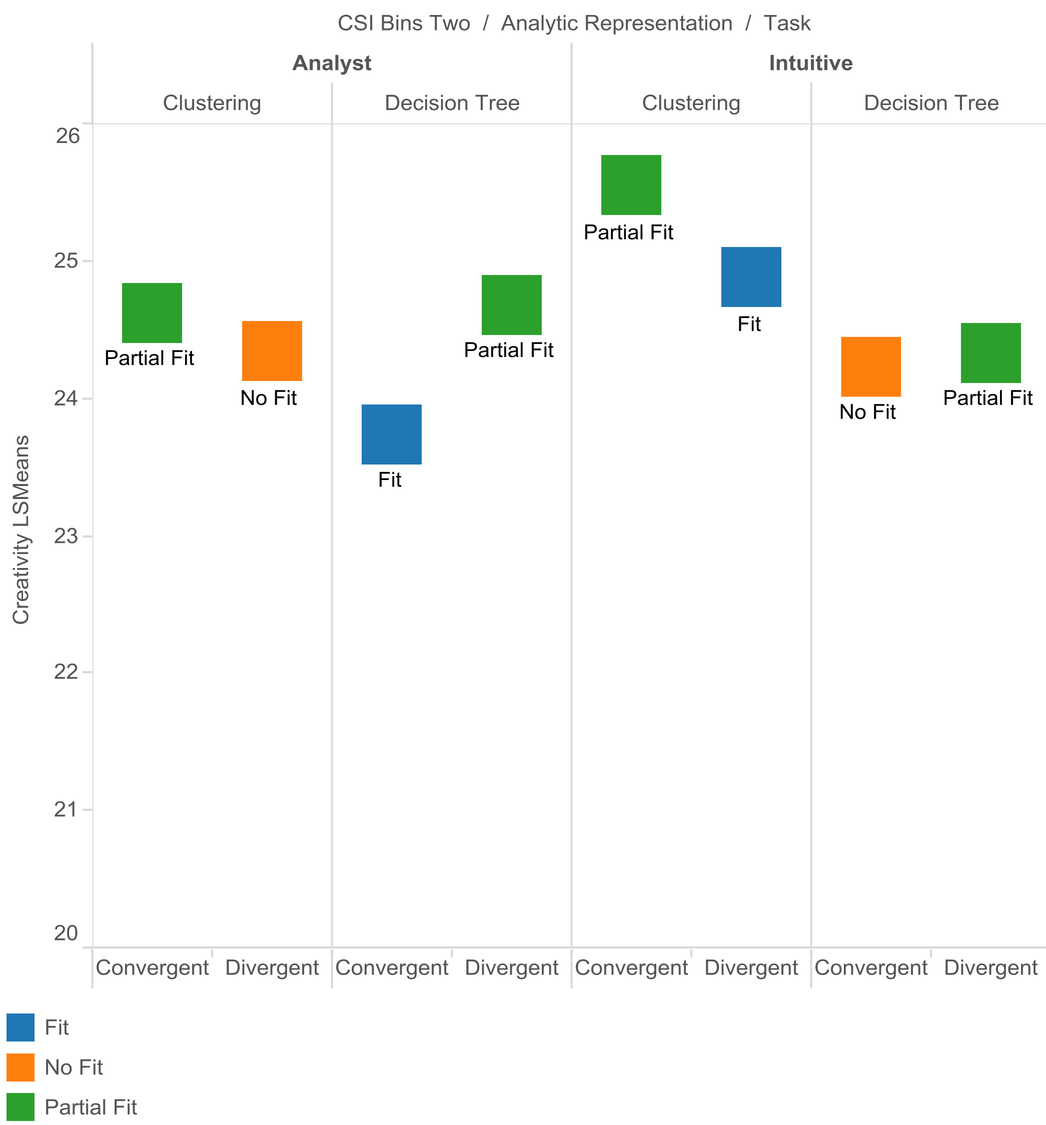


Figure 33: Creativity LSMeans for Three Way Fit

And the plot of all four variables: analytics frames of reference, cognitive style, analytics representation, and task as in figure 34 show that no fit relationship flips between low and high frames of reference. The second thing we notice is that the difference in creativity estimate is larger with low frames than with high frames.

Figure 34: Creativity LSMeans for Three Way Fit with Analytics Frames of Reference

When an analytics frame of reference is low, the difference in creativity between fit and no fit scenarios becomes higher than when an analytics frame of reference is high. The lack of fit between cognitive style and task is stronger than the lack of fit between cognitive style and analytics representation. For example, analyst, decision tree, divergent has stronger effect on creativity than analyst, clustering, convergent; and intuitive, clustering; convergent has stronger effect on creativity than intuitive, decision tree, convergent.

And when we look at the fit scenarios and compare them to the no fit scenarios we find that our hypothesis holds up well in all scenarios except for one (High Frames, Intuitive, Clustering, Divergent). No fit scenarios were always higher than the fit scenarios across all four variables, except one where (High Frames, Intuitive, Clustering, Divergent) fit was higher than no fit. The reason for that one exception might have been that we did not have enough Intuitive subjects in our study.

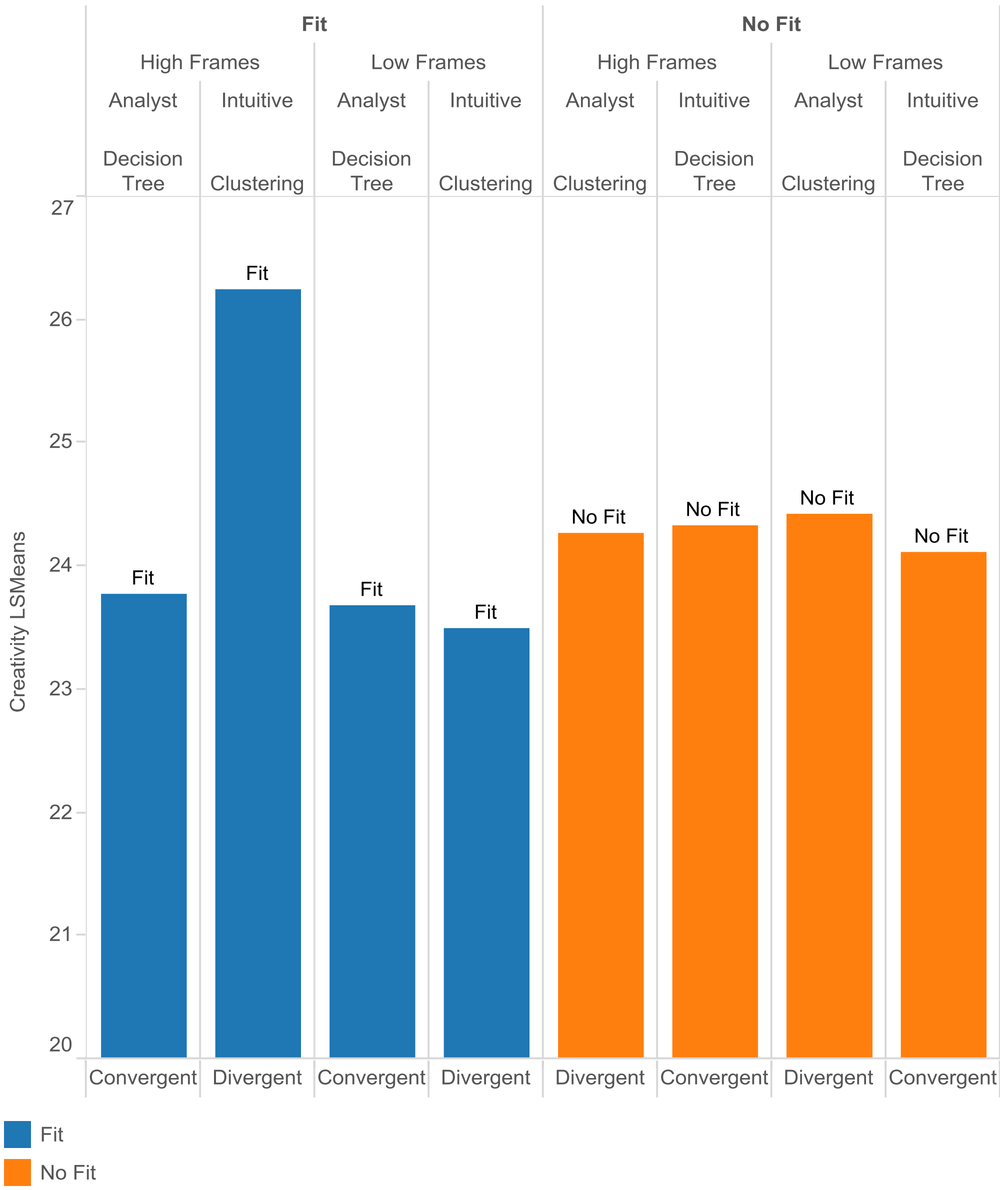


Figure 35: Creativity LSMeans for Fit vs. No Fit Across Four Variables

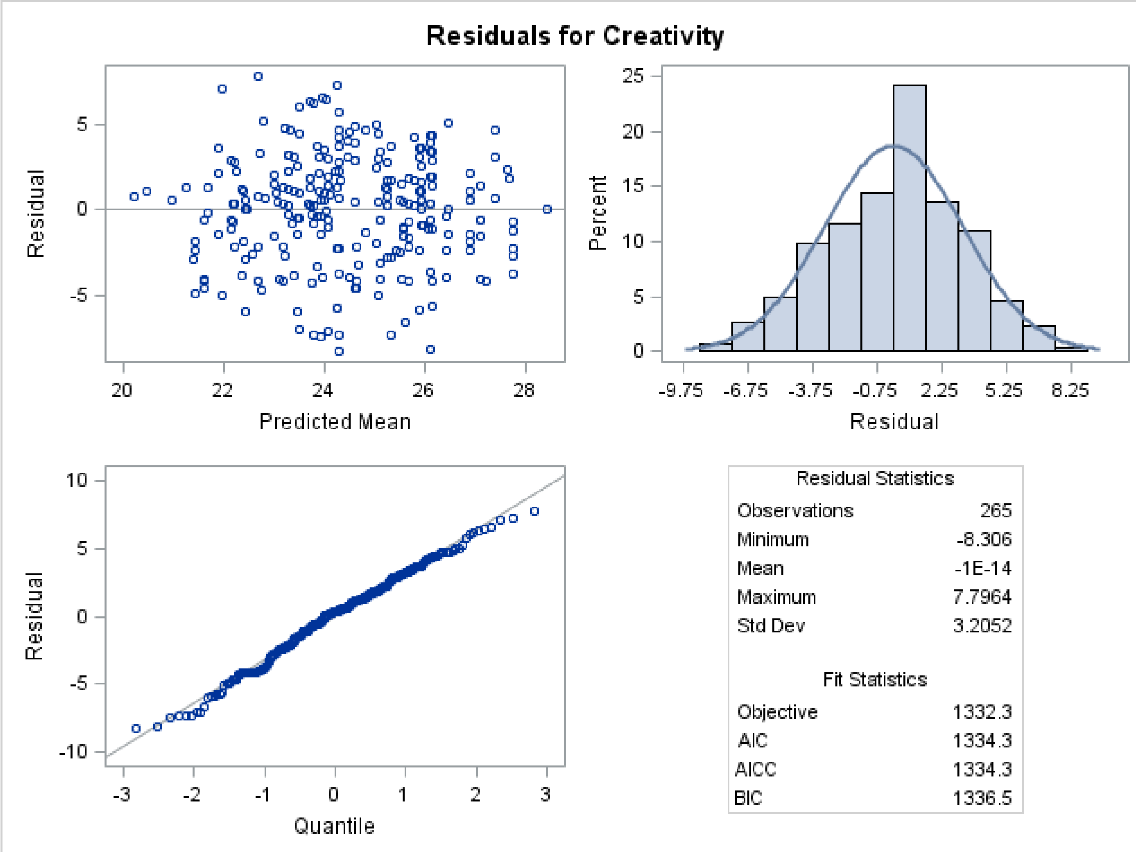


Figure 36: Residuals for Creativity

There were no concerns when we examined residuals (shown in figure 35). The results show that residuals of the full model are normally distributed which validates our model assumptions.

5.4 Full Model (with continuous variables)

Finally, we ran the same model but we replaced: cognitive style categorical variable with the full scale continuous variable, and analytics frames of reference categorical variable with the full scale continuous variable. The model shows strong support to the four-way interaction effect (Task * Analytics Representation * CSI * Analytics Frames of Reference). AIC for this model was 1,493. This model gives support to H2 and H3.

Cognitive style and analytics frames of reference direct effects became highly significant as shown in table 26. And the four-way interaction was the only interaction that was highly significant which provide support to H2 and H3.

We were not able to perform ad hoc analysis using contrast and estimate procedures since there are two continuous variables in the model.

Fixed Effects	P Value
Task	0.1381
Analytics Representation	0.4917
Cognitive Style	0.0006
Analytics Frames of Reference	0.0005

Table 26: Fixed Effects of the Full Model (with continuous variables)

Interactions	P Value
Task * Analytics Representation	0.7295
Task * Analytics Representation * Cognitive Style	0.3982
Task * Analytics Representation * Analytics Frames of Reference	0.3796
Task * Analytics Representation * Cognitive Style * Analytics Frames of Reference	0.0040

Table 27: Interaction Effects of the Full Model (with continuous variables)

5.5 Sensitivity Analysis

We ran sensitivity analysis on the model using analytics frames of reference and cognitive style.

The full model became insignificant when we removed ‘Adaptive’ cognitive style users from the model. Adaptive cognitive style users are defined as having a cognitive style score of between 39 and 45. There were 19 respondents with an ‘Adaptive’ cognitive style, which represents a large number of respondents, hence, the results became insignificant. The fact that we did not get large number of respondents at the two ends of the cognitive style might be one reason we did not get highly significant results for cognitive style variable.

When we excluded ‘Intuitive’ cognitive style subjects and kept only ‘Analyst’, the statistical significance improved and p value became 0.05. When we excluded ‘Analyst’ cognitive style subjects and kept only ‘Intuitive’, statistical significance degraded and p value became 0.11. We had ‘Analyst’ twice as much as ‘Intuitive’, therefore, that might be the reason why ‘Intuitive’ users did not show the results we expected and did not have statistical significance.

The full model became highly significant when we excluded ‘High Frames’ values and kept only ‘Low Frames’ values from the analytics frames of reference variable. ‘Low Frames’ caused the two-way interaction p value to go down from 0.07 to 0.03. When we excluded ‘Low Frames’ and kept only ‘High Frames’ values, the model became insignificant and the p value of the two-way interaction went up from 0.07 to 0.83.

When we examined the three dimensions of analytics frames of reference, we found that the construct had more statistical power than any of the separate dimensions. ‘Analytics Nature’ dimension of analytics frames of reference was highly significant with a p value of 0.0061, ‘Analytics Use’ dimension was significant with a p value of 0.0427, while ‘Analytics Strategy’ dimension was not significant with a p value of 0.3440.

CHAPTER VI

DISCUSSION AND IMPLICATIONS

6.1 Discussion

Our research investigated the relationship between task, analytics representation, cognitive style, and analytics frames of reference and the effect of this relationship on creativity. Our results support the notion that fit in its core definition (task, analytics representation) or in its extended definition (task, analytics representation, cognitive style, analytics frames of reference) have adverse effect on creativity and that no fit or the mismatch between these variables of interest have better effect on creativity.

When we investigated the match between task and analytics representation, there was enough support to show that it had the lowest creativity estimate compared to the scenario when we had a mismatch between task and analytics representation. The match between task and analytics representation has positive effect on efficiency as demonstrated by Vessey, but we showed that it had negative effects on creativity. This match makes it easier to form a mental representation and allow faster comprehension and resolution of the problem at hand, but we showed that it puts the user in a comfort zone and makes it harder to pay attention to cues, therefore users become pre-committed to a decision.

Further examination of the factors influencing fit and its relationship with creativity revealed differences in creativity among the different conditions. The model became stronger with better statistical support when we added the other factors (cognitive style and analytics frames of reference). Results strongly support the fact that analytics frames of reference play a role in moderating the relationship between creativity and fit; and results moderately support the fact that cognitive style has a role in this relationship too.

Analytics frames of reference changes the relationship between fit and creativity. When there is no fit, analytics frame of reference reverses the relationship between no fit and creativity. Analytics frames of reference makes fit more mature; when users have high disposition toward analytics and have high exposure and experience in analytics, fit becomes more mature and its effect on creativity becomes more visible. With low analytics frames of reference, the difference between fit and no fit scenarios becomes higher than when an analytics frame of reference is high. It might be that analytics frames of reference is tapping into the mental representation and helping us reveal some of the factors that influence it.

Cognitive style played a role in the relationship between fit and creativity. The results clearly show that analysts had much higher impact on creativity when they had no fit conditions. We also found that the no fit between cognitive style and task has stronger effect on creativity than the no fit between cognitive style and analytics representation. For example, analyst, decision, divergent has higher creativity estimate in comparison to analyst, clustering, convergent; and intuitive, clustering, convergent has higher creativity estimate in comparison to intuitive, decision tree, convergent.

And as expected, partial fit scenarios had creativity estimates in between no fit and fit conditions. This was true for all eight partial fit scenarios except for the one where intuitive, decision tree, divergent has higher creativity estimate than intuitive, decision tree, convergent.

Cognitive style helped us shed some light on this relationship. We did not have enough ‘Intuitive’ cognitive style subjects and that might be the reason why this variable was not highly supported in our analysis.

6.2 Research Implications

We are examining conditions in which users’ interaction with analytics can promote creativity in decision making. Our research examines how manipulating the analytics outcome can get to better insights. And training users can help create supportive analytics frames of reference.

In the short term cognitive fit can be introduced to enhance adoption of the analytics software, and in the long term it might be beneficial to disrupt cognitive fit to enhance the innovative thinking process. Management should exert efforts in creating an environment in which decision making is facilitated. Some of these efforts should be directed toward identifying human-task fit problems. Management deploying business analytics systems should move away from narrowly focusing on the technical capabilities of the software or on the task characteristics. Attention to the style differences among users can potentially create effective synergies which would enable better decision making quality.

The deployment process, which can find the right fit between decision models and user's abilities, is the enabler of business analytics benefits. We gave insights that can potentially create synergies in the implementations of business analytics, which can increase the decision quality and reduce user's reluctance. And we identified guidelines on how to create a better match between the business analytics software and user cognitive style in different tasks. Using our experiment, we potentially could provide evidence of the importance of the proposed match.

Business analytics software should be flexible enough to give companies the ability to match different capabilities with users and tasks. Designers of business analytics software should be aware of our research model. Our proposed model can potentially help them design software based on cognitive and task factors. And BA software developers should be cognizant of the different performance effects of their software and how to design their software in a way to support a particular outcome.

Our study has extended the cognitive fit theory. First, we have used CEST theory and literature support to shed light on internal representation of problem domain construct in the cognitive fit theory. Our focus on this construct have identified a theoretically founded empirically tested psychometric measurement tool: the cognitive style of users can help future studies in empirically testing the internal representation construct in the cognitive fit theory. Second, although cognitive fit theory has been used in many information systems contexts, our study is still unique in extending the cognitive fit theory into the business analytics deployment domain.

Extant research which addressed this phenomenon was mainly in the eighties of last century and could not use the relatively new psychometric tools used in our study. Moreover, our study applies cognitive fit to business analytics systems and investigates how cognitive fit can affect decision quality.

6.3 Practical Implications

Efficiency or Creativity

Business analytics is mainly used today to allocate resources efficiently. An example is reducing the cost of contacting all customers by contacting customers who are more likely to respond. Another example is allocating bank loans to customers who are less likely to default on loans. Nevertheless, business analytics critical role is in helping management become more innovative by generating insights and becoming creative in their decision making. That is what this research is all about, pointing to the most valuable goal of business analytics by uncovering the conditions that help lead to it.

Companies should be aware of situations in which they need efficiency and situations in which they need creativity. Companies starting to deploy business analytics should exert efforts in finding the best fit, especially at the beginning of the deployment process, in order to ensure better decision making results and overcome deployment hurdles. However, cognitive fit should be disrupted in the long run in order to enhance creativity in the decision making process. Challenge habitual assumptions and apply a different set of components to how you think about problems.

Personalization

Designers of business analytics investigate the data structure to decide on the best analytics methodology to use. Focusing on the data structure and not giving proper attention to the user's cognitive style and the task in hand, makes designers of business analytics lose sight of the ultimate goal of business analytics which is to induce creativity and generate insight. We are proposing that designers should investigate user's cognitive style and the task in hand to decide on the best analytics methodology to use. With today's analytics tools, changing an analytics representation or the analytics methodology has become very easy and accessible.

Companies can use this research to take personalization to an advanced level. Instead of using simple personalization like letting users change the color of a dashboard, we are making personalization more effective by letting users know the best business analytics model and presentation design that fits the way they think and that speaks their language. This research helps in delivering an analytics system that is more effective by attending to users' specific needs. Instead of shooting in the dark and trying different presentation designs, now we are more informed of user's mental needs and can be more effective in achieving specific outcome.

If personalization to each user is difficult, designers can find the cognitive style of the user's majority (i.e. 80% analytical and 20% intuitive) then design for the majority while giving other users alternative options.

Adoption or Abandonment

This research can shed light on business analytics system adoption and user resistance. Future research can extend our study to check the different settings that influence user's decision to use or abandon business analytics.

Langer (2000) talked about mindfulness effect on creativity since it increases the perception of control and increases user's enjoyment of the task.

Choosing the best predictive methodology

Predictive modeling developers get accustomed to one methodology and use that methodology heavily for almost all of their analytics modeling projects. I work as an analytics consultant and have seen this in real world. My colleagues at work are very proficient with logistic regression and have been using it for years. I have asked one of the consultants on the reason they all use the same method over and over and his response was that Logistic has proven very successful with the type of problems they face and the data structure they have; decision tree can do the same thing with similar level of precision and accuracy so why bother! This is risky; first, it proves that developers do not consider the different presentation output coming out of different algorithms. Designers of analytics make their analytics modeling choice based on the data structure and the dependent variable type, without consideration to user's interaction with the analytics output and how that affects insight generation. Second, when designers use the same modeling algorithm there is a hidden risk in using the same presentation output to users. If we want users to be creative and find new insights then users need to break out of the conventional design space, cognitive science has developed to tell us about cognitive fit, mindfulness, and performance.

CHAPTER VII

FUTURE RESEARCH

7.1 Contribution

This research paper is unique in many aspects. First, our main focus is on business analytics and creativity. Our research builds on the theory of cognitive fit to examine the role it can play in enabling user understanding and processing of different DSS models and tasks. Extant research looked at user's cognitive style effect -- and not cognitive fit effect -- on perception and intention to use DSS systems (Chakraborty et al., 2008), (Hsi-Peng Lu et al., 2001). Second, extant research looked at technology acceptance and system use as the dependent variable (Chakraborty et al., 2008), (Hsi-Peng Lu et al., 2001), while we will look at creativity and decision quality as the ultimate effect of cognitive fit.

Third, our research will extend the cognitive fit theory by crystallizing internal representation with the cognitive styles of individuals. We build on the new advances in cognitive science and use Allinson and Hayes relatively new psychometric tool developed for organizations (Allinson & Hayes, 1996). The role of cognitive styles has not been explored by cognitive fit theory. Fourth, this research will address the new business analytics models and tasks rather than the traditional decision sciences models and tasks. Our research context is business analytics and the latest data mining models and applications which represent an important trend in information systems. Up to our knowledge, no one has explored the effect of cognitive fit on decision quality in the context of DSS or business analytics.

Creating an Environment for Business Analytics Success

This research aims at finding better ways to implement business analytics. We posit that creating an environment which promotes synergy between user abilities and needs along with business analytics capabilities is the key to successful deployment of business analytics. If model representations match user cognitive style, then this will enhance user's understanding of the problem. A greater portion of user cognition efforts will be directed toward solving the problem rather than struggling to understand it. When the match does not happen, that can also be beneficial since it can enhance the creativity of users in solving problems. Additionally, promoting the role of business analytics among users can enhance cognitive fit influence on performance. This research will complete the analytics process by finding techniques which can allow users to augment the technical outputs with their human abilities and expertise. When users' have exposure to business analytics and are educated on the role of business analytics, then that will enhance performance effects.

7.2 Limitations

The first limitation of this study was around sample size. Although we had good sample size (69 subjects with valid responses), we might have had better statistical significance with larger sample size. Mainly because we had four interacting variables and need enough subjects in each cell of the conditions we had. We did not get good number of subjects that are 'Intuitive' cognitive style, nor enough subjects with 'High Frames' of the analytics frames of reference. Maybe if we had enough, these two variables would have had higher statistical significance across all scenarios of fit. We worked with Qualtrics Panel to get analytics consultant to do the experiment and out of 150 responses we were only able to use 69.

The second limitation would be around the repeated measures on each subject. It would be interesting to check the effect of these different fit conditions using one task per subject. But this would need a much larger sample size to be able to get enough subjects in each experiment cell.

Another limitation is that we only investigated decision tree and clustering from the variety of analytics representations that could have been investigated. These two were chosen because they represent two contrasting modes of representations one with a clear spatial component (clustering) and the other with a numerical component (decision tree). Future studies could empirically test the studied relationships using other analytics representations like regression trends.

CHAPTER VIII

CONCLUSION

We examined enhancing insight generation and creativity through the different interaction settings. We acknowledge the fact that technical specifications of the problem might limit the wide selection of model representations. However, after the problem passes the technical specification limits, users have a choice in selecting an appropriate model representation. And we promote that the behavioral specifications provided in this study should guide this selection.

DeWaele (1978) argued that matching DSS with manager's cognitive style might reinforce previous biases and create blind spots in making decisions. However, DeWaele was aware that managers are not likely to use tools that are inconsistent with the way in which they think. Sprague and Carlson(1982) and Brightman, Elrod, and Ramakrishna (1988) posit that change should be evolutionary not revolutionary. Thus, we conclude that managers should be trained on tools that support their cognitive style first. Once managers absorb this tool and the deployment project is successful, then managers should be trained on tools that support their opposite cognitive style to help boost creativity. For example, finance managers are characterized by an analytical dominant style (Allinson &

Hayes, 1996), deploying analytics to them should start with analytical models to ensure adoption, once the process is successful then other models can be introduced appropriately to ensure creativity.

While business analytics software has reached advanced technical levels, the deployment process is still at its infancy. There is much research needed in the area of business analytics deployment. A deployment process which promotes a whole brain approach of users and can take advantage of all our cognitive abilities as decision makers.

Several strides are needed in the future in order to bridge the gap between business analytics software and users.

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APPENDIX

Appendix-A Research Instrument

Informed Consent:

Thank you in advance for completing this survey, we really appreciate your time.

My name is Tarek Soukieh. I am a doctorate student at Cleveland State University, and this is part of my dissertation research project.

This research will help us understand the different performance effects of using advanced analytics techniques. It will also help in advancing our knowledge on the way humans interact with advanced analytics output which would lead to a creative outcome. Risks involved in this study include minor discomfort or inconvenience from spending the time needed to complete the survey in front of the computer. Participants might feel some discomfort in using their judgments and evaluations of different analytics output scenarios. For questions or comments on this survey, please do not hesitate to contact me Tarek Soukieh at (216) 482-7117 or Dr. Ray Henry at (216) 687-4785.

This survey should take you around 30 minutes. We will not collect any personally identifiable information and we are not enabling any web tracking or online behavior analysis. Your participation is voluntary and you can withdraw at any time without penalty. Results will be published as part of the dissertation research. Information will be presented and communicated in aggregates. Respondents cannot be identified, and the reminder email for participation will be sent to all potential participants.Please note that there are no direct benefits to be accrued by individuals participating in this survey.

"I understand that if I have any questions about my rights as a research subject I can contact Cleveland State University Institutional Review Board at (216) 687-3630"

Please choose one from the following two options:

- ◯ I consent. Please continue.
- ◯ I do not consent. Please cancel my participation.

Definitions:

Business Analytics Systems encompass the people, processes, and technologies involved in the gathering, analysis, and transformation of data used to support managerial decision making.

Business Analytics Systems is also known as the use of advanced statistical analysis tools to discover patterns, predict trends, and optimize business processes.

How many years of experience do you have with Business Analytics?

- ◯ No experience at all.
- ◯ 1-2 years of experience
- ◯ 3-5 years of experience
- ◯ 6-10 years of experience
- ◯ >10 years of experience

How many times have you used (or been exposed to) decision tree in the past?

- ◯ None
- ◯ Once
- ◯ Twice

Three times or more

How many times have you used (or been exposed to) clustering in the past?

- None
- Once
- Twice
- Three times or more

What is your age?

What is your gender?

- Male
- Female

Please indicate your occupation:

What is the highest level of education you have completed?

- Less than High School
- High School / GED
- Some College
- 2-year College Degree
- 4-year College Degree
- Masters Degree
- Doctoral Degree
- Professional Degree (JD, MD)

The position you currently hold:

- Executive
- Manager
- Supervisor
- Analyst
- Individual Contributor

How many years of professional experience do you have?

- No experience at all.
- 1-2 years of experience
- 3-5 years of experience
- 6-10 years of experience
- >10 years of experience

People differ in the way they think about problems. Below are 19 statements designed to identify your own approach. If you believe that a statement is true about you, answer T. If you believe that it is false about you, answer F. If you are uncertain whether it is true or false, answer ?. This is not a test of your ability, and there are no right or wrong answers. Simply choose the one response which comes closest to your own opinion. Work quickly, giving your first reaction in each case, and make sure that you respond to every statement.
Indicate your answer by completely filling in the appropriate oval opposite the statement:

	T	?	F
In my experience, rational thought is the only realistic basis for making decisions.	○	○	○
To solve a problem, I have to study each part of it in detail.	○	○	○
I am most effective when my work involves a clear sequence of tasks to be performed.	○	○	○
I have difficulty working with people who 'dive in at the deep end' without considering the finer aspects of the problem.	○	○	○
I am careful to follow rules and regulations at work.	○	○	○
I avoid taking a course of action if the odds are against its success.	○	○	○
I am inclined to scan through reports rather than read them in detail.	○	○	○
My understanding of a problem tends to come more from thorough analysis than flashes of insight.	○	○	○
I try to keep to a regular routine in my work.	○	○	○
The kind of work I like best is that which requires a logical, step-by-step approach.	○	○	○
I rarely make 'off the top of the head' decisions.	○	○	○
I prefer chaotic action to orderly inaction.	○	○	○
Given enough time, I would consider every situation from all angles.	○	○	○
To be successful in my work, I find that it is important to avoid hurting other people's feelings.	○	○	○
The best way for me to understand a problem is to break it down into its constituent parts.	○	○	○
I find that to adopt a careful, analytical approach to making decisions takes too long.	○	○	○
I make most progress when I take calculated risks.	○	○	○
I find that it is possible to be too organised when performing certain kinds of task.	○	○	○
I always pay attention to detail before I reach a conclusion.	○	○	○

Please write the word "survey" in the box below just to make sure that you are paying attention:

Below are the other 19 statements. Please indicate your answer by completely filling in the appropriate oval opposite the statement:

	T	?	F
I make many of my decisions on the basis of intuition.	○	○	○
My philosophy is that it is better to be safe than risk being sorry.	○	○	○
When making a decision, I take my time and thoroughly consider all relevant factors.	○	○	○

I get on best with quiet, thoughtful people.	○	○	○
I would rather that my life was unpredictable than that it followed a regular pattern.	○	○	○
Most people regard me as a logical thinker.	○	○	○
To fully understand the facts I need a good theory.	○	○	○
I work best with people who are spontaneous.	○	○	○
I find detailed, methodical work satisfying.	○	○	○
My approach to solving a problem is to focus on one part at a time.	○	○	○
I am constantly on the lookout for new experiences.	○	○	○
In meetings, I have more to say than most.	○	○	○
My 'gut feeling' is just as good a basis for decision making as careful analysis.	○	○	○
I am the kind of person who casts caution to the wind.	○	○	○
I make decisions and get on with things rather than analyse every last detail.	○	○	○
I am always prepared to take a gamble.	○	○	○
Formal plans are more of a hindrance than a help in my work.	○	○	○
I am more at home with ideas rather than facts and figures.	○	○	○
I find that 'too much analysis results in paralysis'.	○	○	○

Please indicate how much you agree with each of the following statements:

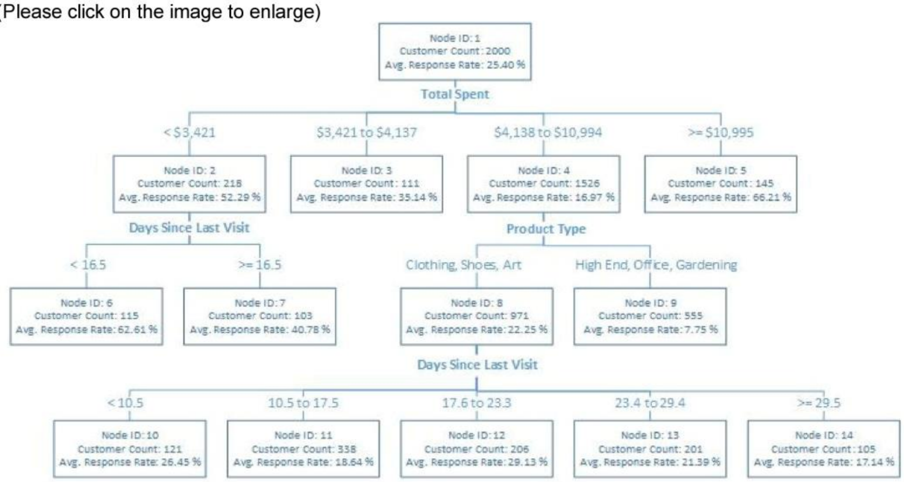
	Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Agree	Strongly Agree
I know what business analytics represents	○	○	○	○	○	○	○
I understand business analytics capabilities	○	○	○	○	○	○	○
I know nothing about business analytics	○	○	○	○	○	○	○
I am aware of the nature of business analytics	○	○	○	○	○	○	○
Business analytics is rich in capabilities	○	○	○	○	○	○	○
I understand why organizations adopt business analytics	○	○	○	○	○	○	○
I am aware of the motivation behind adopting business analytics	○	○	○	○	○	○	○
Business analytics helps companies achieve their strategies	○	○	○	○	○	○	○
Business analytics has the potential to transform the way we do business	○	○	○	○	○	○	○
Business analytics helps managerial decision making	○	○	○	○	○	○	○
I know how business analytics is used in organizations	○	○	○	○	○	○	○
I am aware of the conditions associated with business analytics use	○	○	○	○	○	○	○
I know how business analytics is used down to a granular level	○	○	○	○	○	○	○
Business analytics is used to help support day to day operational decisions	○	○	○	○	○	○	○
I am aware of the different business analytics functionalities	○	○	○	○	○	○	○
To show that you have been paying attention please select Disagree	○	○	○	○	○	○	○

All-Mart sells a variety of products (clothing, shoes, office, gardening, art, high end) in its 350 retail locations. You have data on the previous marketing campaigns and how each customer responded to it, plus how much each customer spent, and how long each customer has been with your company. The following is the data set used:

NAME	ROLE	DESCRIPTION
CustomerID	ID	Customer Identifier
Days Since Last Visit	Input	Number of days since the customer made the last purchase
Product Type	Input	Product type marketed in the campaign
Response	Target	Did the customer make a purchase after receiving the marketing campaign (Y/N)
Total Spent	Input	Total amount spent by the customer on all purchases

The data mining software ran decision tree analysis on your customer data and identified the following classifications tree for your customers:

(Please click on the image to enlarge)



- Avg. Response Rate: number of customers who responded positively to the last marketing campaign / total number of customers

You are helping the marketing function develop a marketing campaign that would attract customers with the highest potential.

Using the above decision tree:
1) Identify the group of customers with the highest potential
2) Describe **why** you chose this group

Please note the following when answering the question:
1) Be **creative** in identifying this group of customers
2) Be **descriptive** in your answer and give enough explanation
3) Your answer should be based specifically on the above decision tree
4) Your identified group of customers can span one or more decision tree

Using the above decision tree:
1) Identify a list of only creative (uncommon, out of the normal) uses of the decision tree results that can help the organization in ways other than in marketing campaigns
2) Describe what specifically in the visual display helped you in each suggestion

Please note the following when answering the question:
1) Be **creative** in identifying other uses of the results
2) Be **descriptive** in your answer and give enough explanation
3) Your answer should be based specifically on the above decision tree

Clustering Block

These page timer metrics will not be displayed to the recipient.

First Click: *0 seconds*

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All-Mart sells a variety of products (clothing, shoes, office, gardening, art, high end) in its 350 retail locations. You have data on the previous marketing campaigns and how each customer responded to it, plus how much each customer spent, and how long each customer has been with your company.

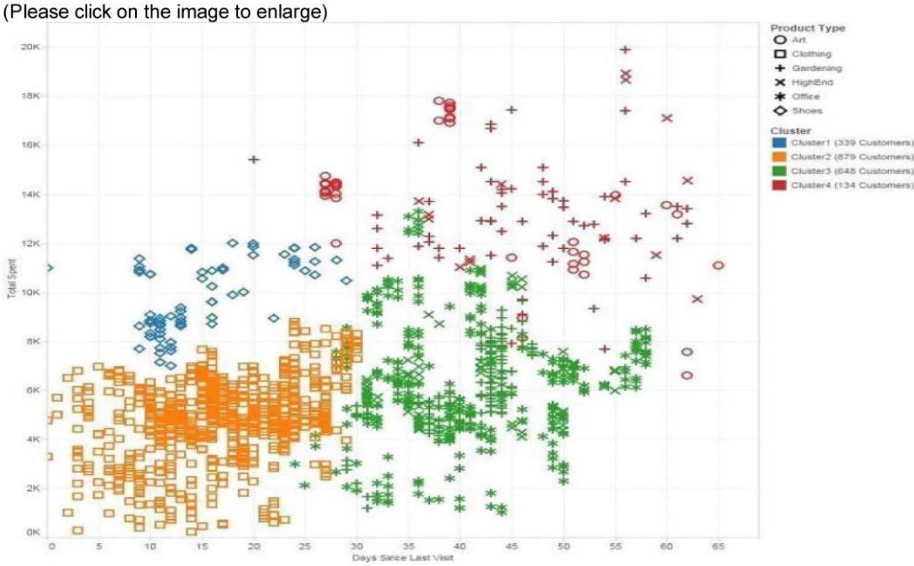
The following is the data set used:

NAME	ROLE	DESCRIPTION
CustomerID	ID	Customer Identifier

Days Since Last Visit	INPUT	Number of days since the customer made the last purchase
Product Type	INPUT	Product type marketed in the campaign
Response	INPUT	Did the customer make a purchase after receiving the marketing campaign (Y/N)
Total Spent	INPUT	Total amount spent by the customer on all purchases

The data mining software ran cluster analysis on your customer data, and identified the following clusters for your customers:

(Please click on the image to enlarge)



You are helping the marketing function develop a marketing campaign that would attract customers with the highest potential.

Using the above clustering diagram:
1) Identify the group of customers with the highest potential
2) Describe **why** you chose this group

Please note the following when answering the question:
1) Be **creative** (uncommon, out of the normal) in identifying this group of customers
2) Be **descriptive** in your answer and give enough explanation
3) Your answer should be based specifically on the above clustering diagram
4) Your identified group of customers can span one or more clusters

Using the above clustering diagram:
1) Identify a list of only creative (uncommon, out of the normal) uses of the clustering results that can help the organization in ways other than in marketing campaigns
2) Describe what specifically in the visual display helped you in each suggestion

Please note the following when answering the question:
1) Be **creative** in identifying other uses of the results
2) Be **descriptive** in your answer and give enough explanation
3) Your answer should be based specifically on the above clustering diagram