Engaging Experts: Overcoming Trust in Risky Environments

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Engaging Experts: Overcoming Established Trust in Risky Environments

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Abstract

In business-to-business sales environments, sellers may choose to bring their go-to expert to a customer meeting, even when there is an expert available who may be more skilled in the product being discussed. The purpose of this study is to identify if an intervention of data, trust transference, ingroup identity, or a combination, influence the choice of expert a salesperson engages for a customer meeting. We tested this question through a series of vignettes and hierarchical linear modeling. The sample came from a US-based technology company, and salespeople in the United States.

We found that trust transference influenced both choice in the expert as well as trust in the expert chose. The intervention of data influenced choice in the expert. Ingroup identity was not a factor in either choice or trust in the expert. The findings or lack of findings on the impact of ingroup identity merit additional research as it is contrary to previous findings. Additionally, this study shows that individuals may use the same factors in decision-making as they articulate in other situations about that decision. Academic research like this can reveal true decision-making behavior. Finally, managers should invest in trust-building activities with their teams and encourage them to share knowledge of resources and experts. After building trust between team members, transfer of trust becomes a powerful tool in organizations to influence speed and trust in decision-making.
Acknowledgements

For good or for bad, curiosity has consumed most of my existence on this planet. I have found almost everything fascinating and have collected so many questions along this journey. Most of my work-life has centered around technology and people. It seems that most technical questions have answers, but so many of the people questions do not. I set on this doctoral journey to accomplish two things: 1) learn to ask better questions, and 2) learn how to answer them. The DBA program at UMSL has helped me accomplish both objectives. But it’s the people around me who have made it possible.

First, I’d like to thank my committee, Dr. Breaugh, Dr. Meriac, and especially Dr. Merritt. Your insights, patience, and guidance to complete this final dissertation were not only invaluable, but so necessary and informative. I am grateful for your support and encouragement. Next, I thank my peers in the DBA cohort. We worked together to make this happen. My greatest wish is that we continue to work together to debate new topics and add to both practitioner and academic knowledge.

Finally, I thank my husband Brian, and my children, Caden and Maya. As a working parent and spouse, our family time is on the evenings and weekends. I gave so much of our family time to this pursuit. I’ll be forever grateful to you all for allowing me this opportunity to build new skills that power my own future and curiosity, as I’m also responsible for helping you build yours. Caden and Maya, I wish to give you the same opportunity in the future to fuel your own dreams. Brian, you are more than a partner in life, you are an inspiration and a role model. I am grateful to you for your incredible support and patience.
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Chapter 1: Introduction

Research Question and Importance

High tech is a massive industry. Globally, companies spend approximately $4 trillion on Information Communication and Technology (ICT) technologies, forecasted to grow to $5.8 trillion by 2023 (IDC: Forecast 2020-2023, 2020). While companies spend a significant amount on this technology, the traditional ICT market has a somewhat low growth rate of around 3-5% per year (IDC: Forecast 2020-2023, 2020). Relatively few key players dominate the industry. The “Big Five” technology companies, Amazon, Apple, Alphabet, Microsoft, and Meta, generate approximately $900 billion annually, or about one-quarter of the total market (How Big Tech Makes Their Billions, 2020). With a low growth rate and relatively few market players, that leaves large high-tech companies fighting for market share in a dwindling traditional market.

In the battle over the business-to-business share of the ICT market, each technology company needs to position its best talent in the sales process to win each deal. As part of the sales process, the lead salesperson typically chooses a technical expert to address customers’ technical questions. The organization employs a broad set of technical experts who are more familiar with some products than others. The sales effort could fail if the salesperson selects a technical expert who fails to impress the customer’s technical team. The problem: salespeople's human preferences, heuristics, and biases may prevent them from leveraging the technically best experts within their firms to win a customer’s business. Instead, they prefer to work with “known” experts (experts they have worked
with previously) regardless of whether the known expert is the best technical fit for the sales effort. This behavior may lead to a loss in a firm’s sales and market share.

Based on this problem, this study's primary research question was: can an intervention of data, trust transference, ingroup identity, or a combination, influence the choice of expert a salesperson engages for a customer meeting?

**Background Information**

A key determinant in a firm’s success in business-to-business (B2B) exchanges is their salesperson’s ability to match the customer business needs to the firm’s products (Shi et al., 2017). To do so, the firm’s salesperson conducts one or more sales meetings with customer representatives. Typically, a salesperson develops an ongoing relationship with their customers. The salesperson plays a vital role in the relationship with the customer in business-to-business transactions, influencing customer retention and buying intentions (Johnson et al., 2001). Complex B2B sales start with a seller-customer relationship within the ICT market where the seller and customer develop a close, interpersonal connection (Newell et al., 2011). That connection significantly influences intention to purchase, trust in the seller, and positive future buying intentions (Bateman & Valentine, 2015). Thus, sellers find great value in maintaining healthy and positive customer relationships.

In building a relationship and establishing credibility with the customer, the ICT sales team must provide high-quality answers to technical questions raised by the customer’s technical experts. The customer decision-maker may have a technical background or bring in their own technical expert to validate the selling firm’s product/solution technical capabilities. In many cases, the salesperson (seller) does not
possess sufficient technical expertise to address the customer’s technical questions and concerns. Therefore, sellers frequently must find and engage their technical experts to help them with these customer conversations.

Getting the right expert engaged with a customer as quickly as possible is critical to customer satisfaction and capturing their attention. The customer may want to know how the technology will fit into their current technology environment. How will the technology solve their business problem or enhance their business environment? How is the technology uniquely qualified to accomplish these goals? How is it better than a competitor’s technology? In high technology firms with large portfolios and numerous products/solutions, the seller is often a “generalist” and cannot answer these questions about the individual solutions’ specific capabilities. So, the seller must solicit help from a technical expert in the sales process. See Figure 1.1 for an example of the process. The technical expert’s role is to define the capabilities of the firm’s solutions, position competitive superiority, and link the firm’s product to the customer’s business challenge (Goodwin-Sak, 2019). In a large firm with many technical products, the firm has several technical experts on staff who vary in their level of familiarity with the various products in its portfolio. The salesperson may have multiple experts to help address the customer’s needs.
Figure 1.1

Example of the Sales Process

**The initial meeting.**
Seller Joe is meeting with Customer Amanda to discuss her business challenges. Both Seller Joe and Customer Amanda have ideas on how to solve Amanda’s business challenges with technology. Customer Amanda wants to
1. Validate the technical superiority of Seller Joe’s products over those from other vendors
2. Ensure that the products have the features required to solve the business challenge
3. Will integrate into their existing technical environment.
They schedule a follow-up meeting with their technical experts.

**The follow-up meeting.**
Seller Joe brings his trusted expert, Engineer Sam, to the meeting to answer deep technical questions from Engineer Adam on:
1. The technical comparison of Seller Joe’s products over those from other vendors
2. The features required to solve the business challenge
3. The integration capabilities for the current environment.

When selecting a technical expert, the seller faces dual pressures to a) impress the buyer team with technical expertise and b) build or maintain interpersonal rapport with the customer. Often, technical experts are stereotyped with high technical skills and low interpersonal skills (Akbulut-Bailey, 2013; Enns et al., 2006; Galetta, 2007). There is a concern in the seller’s mind that the expert will not understand how to read the customer environment, respond appropriately, and adequately address situations when a customer
asks a question to which the expert has no answer (Goodwin-Sak, 2019). Some of the technical experts in the pool are known to the sellers (i.e., they have worked together on previous sales pitches), while some are unknown. Once a seller has determined that a particular expert has good interpersonal skills, the seller feels a desire to continue working with that “known” expert rather than taking a chance on someone who may be a better technical fit but has unknown interpersonal skills (Goodwin-Sak, 2019).

Trust is often fragile at the beginning of an interpersonal relationship or in times of perceived high risk (McKnight et al., 1998). If a seller perceives that their relationship with the customer is weak or at risk, they may fear introducing an unknown expert to the customer. Bringing an unpleasant or interpersonally unskilled technical expert to a sales meeting is perceived as risky – a poor choice of technical expert could result in losing the sale and its associated commission and damaging the quality of the relationship between the seller and the customer (Goodwin-Sak, 2019).

The seller’s vulnerability to financial losses and the uncertainty around how the unknown expert will behave in front of the customer make trust a key element in the seller’s decision-making process. When presented with the choice of introducing a trusted expert or an unknown expert to the customer, regardless of technical capability, sellers report being more likely to choose the known expert to control risk (Goodwin-Sak, 2019; Granovetter, 1973). Without intervention, a lack of trust in an expert may encourage a seller to bring in a less qualified expert, potentially harming firm revenue and market share.

This study’s primary goal was to develop an intervention leveraging trust transference and quantitative data to encourage a seller to engage with the most highly
qualified technical expert for a given project, even when that expert was not previously known to the seller. We believed the intervention was best tested in the form of an experiment and conducted at a technology company, Cisco, to most closely replicate the scenario defined above. The following chapter reviews existing literature on establishing trust between two parties and potential methods for overcoming negative stereotypes. This literature serves as the theoretical foundation for the intervention that was developed, concluding with a discussion of the study's potential contributions.
Chapter 2: Literature Review

The literature review for this study covers multiple facets of the observed behaviors that instigated this study. As the context of these behaviors is grounded in trust between the seller and the expert, we begin our literature review with trust.

Defining Trust

While trust is a widely used term in academic research, there is no generally accepted definition. Deutsch (1958) defined trust using words such as “expectation,” “predictability,” and “motivational relevance.” This definition incorporates the concept of risk in the actor failing to meet expectations. Giffin (1967) evolved the definition of trust to include risk-taking inherently. Giffin’s definition is “reliance upon the characteristics of an object, or the occurrence of an event, or the behavior of a person to achieve a desired but uncertain objective in a risky situation” (p. 105). Rousseau et al. (1998) performed a qualitative analysis of trust literature and created a trust definition that reflects the most common characteristics of trust definitions in the literature. Their definition is “[t]rust is a psychological state comprising the intention to accept vulnerability based upon positive expectations of the intentions or behavior of another” (p. 395). This definition includes the concept of risk, interdependence, and “willingness to be vulnerable” (p. 395), common in much of the literature on trust. Rousseau et al.’s definition also reflects the belief of McKnight et al. (1998) that trust can be broken into two constructs: trusting intentions and trusting beliefs.

Walterbusch et al. (2014) performed a qualitative and quantitative analysis of the literature, focusing on trust definitions. Based on the word frequency and citation frequency of the definitions of trust, they found the most-cited definition was that of
Whitener et al. (1998): “First, trust in another party reflects an expectation or belief that the other party will act benevolently. Second, one cannot control or force the other party to fulfill this expectation. Trust involves a willingness to be vulnerable and risk that the other party may not fulfill that expectation. Third, trust involves some level of dependency on the other party so that the outcomes of one individual are influenced by the actions of another” (p. 513). Refer to Table 2.1 for a list of trust definitions reviewed.

Because there are many different definitions of trust in academic literature, and one definition encompasses the most commonalities of other definitions, we used the definition created by Whitener et al. (1998) in this study. This definition’s key features include risk, vulnerability, interdependence, and benevolence; benevolence is the trustee’s willingness to help the trustor (Mayer et al., 1995). As applied to the seller-expert context, risk refers to the possibility of financial loss, while vulnerability refers to the notion that the likelihood of making the sale (and earning commission) can be affected by the technical expert’s performance. The seller depends on the expert to provide expertise to the customer and relies on the expert’s benevolence to have the seller’s best interest in mind by demonstrating technical competence and social adaptability.
Table 2.1

*Trust Definitions*

<table>
<thead>
<tr>
<th>Year</th>
<th>Author</th>
<th>Definition</th>
<th>Key Concepts</th>
</tr>
</thead>
<tbody>
<tr>
<td>1967</td>
<td>Rotter</td>
<td>An expectancy held by an individual or a group that the word, promise, verbal, or written statement of another individual or group can be relied on.</td>
<td>Expectation; reliance</td>
</tr>
<tr>
<td>1967</td>
<td>Giffin</td>
<td>Reliance upon the characteristics of an object, or the occurrence of an event, or the behavior of a person in order to achieve a desired but uncertain objective in a risky situation.</td>
<td>Expectations; reliance; risk</td>
</tr>
<tr>
<td>1995</td>
<td>Mayer et al.</td>
<td>The willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other part.</td>
<td>Vulnerability; reliance</td>
</tr>
<tr>
<td>1998</td>
<td>McKnight et al.</td>
<td>One believes in, and is willing to depend on, another party. Includes trusting beliefs and trusting intentions.</td>
<td>Inter-dependence; trusting beliefs and intentions</td>
</tr>
<tr>
<td>1998</td>
<td>Rousseau et al.</td>
<td>Trust is a psychological state comprising the intention to accept vulnerability based upon positive expectations of the intentions or behavior of another</td>
<td>Vulnerability; trusting beliefs and intentions</td>
</tr>
<tr>
<td>1998</td>
<td>Whitener et al.</td>
<td>First, trust in another party reflects an expectation or belief that the other party will act benevolently. Second, one cannot control or force the other party to fulfill this expectation – that is, trust involves a willingness to be vulnerable and risk that the other party may not fulfill that expectation. Third, trust involves some level of dependency on the other party so that the outcomes of one individual are influenced by the actions of another</td>
<td>Expectation; benevolence; vulnerability; risk; inter-dependence</td>
</tr>
<tr>
<td>1985</td>
<td>Lewis &amp; Weigert</td>
<td>Interpersonal trust has cognitive and affective components</td>
<td>Cognitive; affective</td>
</tr>
<tr>
<td>Year</td>
<td>Author</td>
<td>Definition</td>
<td>Key Concepts</td>
</tr>
<tr>
<td>------</td>
<td>----------------------</td>
<td>-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
<td>-----------------------------</td>
</tr>
<tr>
<td>2018</td>
<td>Luhmann</td>
<td>Familiarity is the pre-condition for trust and distrust.</td>
<td>Familiarity</td>
</tr>
<tr>
<td>1985</td>
<td>Rempel et al.</td>
<td>Predictability and dependability require a consideration of the impact of past experience and reliability of previous evidence.</td>
<td>Predictability; dependability; experience</td>
</tr>
<tr>
<td>2005</td>
<td>Johnson &amp; Greyson</td>
<td>Knowledge is accumulated from observation of partner behavior within the focal relationship and from reported reputation in other relationships. When reputation effects are strong, initial interactions may be merely an opportunity to confirm or disconfirm prior perceptions, and cognitive trust may become definitive in one or a few interactions.</td>
<td>Experience; reputation confirmation</td>
</tr>
<tr>
<td>2005</td>
<td>Johnson &amp; Greyson</td>
<td>Affective trust is the confidence one places in a partner on the basis of feelings generated by the level of care and concern the partner demonstrates. The essence of affective trust is reliance on a partner based on emotions. As emotional connections deepen, trust in a partner may venture beyond that which is justified by available knowledge.</td>
<td>Feelings; emotions</td>
</tr>
<tr>
<td>1995</td>
<td>McAllister</td>
<td>Findings from attribution research indicate that behavior recognized as personally chosen rather than role-prescribed, serving to meet legitimate needs, and demonstrating interpersonal care and concern rather than enlightened self-interest may be critical for the development of affect-based trust</td>
<td>Interpersonal care</td>
</tr>
</tbody>
</table>
Cognitive Trust vs. Affective Trust

There are different foundations of trust – one based on cognition and one based on affect (Lewis & Weigert, 1985). In the absence of trust, an individual must make a complex series of predictions on various situations' likely outcomes. Trust allows us to simplify the decision-making process, essentially providing a heuristic to inform behavior.

Cognitive trust is built upon assessments of the partner’s level of competence. It is related to predictability and reliability (Johnson & Grayson, 2005; Johnson-George & Swap, 1982; Rempel et al., 1985). Familiarity is a frequently cited factor for trust, and thus, cognitive trust is built over time through experience with another individual (although reputation can also affect cognitive trust; Johnson & Grayson, 2005; Luhmann, 2018). We achieve cognitive trust when there is no further need to justify confidence in another for the given context. In other words, trust is formed when uncertainty decreases in how the other will behave in a given context (Lewis & Weigert, 1985). In the seller-expert partnership, the seller’s cognitive trust is associated with both the expert’s technical competence (level of expertise with the specific solution proposed) and interpersonal competence (communication skills; listening skills; relationship-building skills; Goodwin-Sak, 2019). In the context of this research, sellers have developed high cognitive trust in their go-to technical experts through past interactions in the selling environment/customer meetings.

---

1 While cognitive trust is known to require time to develop, researchers have found it to be a solid target for developing Swift Trust, a concept that is addressed later in this paper. Cognitive trust is the foundation upon which we for most of our manipulations in the experiments designed to answer our research question.
Affective trust, or emotional trust, is based on the level of care, concern, and benevolence the partner demonstrates. It is also developed in the context of a relationship and reputation (Johnson & Grayson, 2005; Lewis & Weigert, 1985). Higher levels of affective trust are related to feelings of security and the relationship's strength (Johnson & Grayson, 2005). Cognitive and affective trust are not mutually exclusive, but cognitive trust in a coworker may predict affective trust (McAllister, 1995). In a work setting, coworkers may develop affective trust or personal caring for one another. In this setting, an interpersonal bond is created where a breach of trust would inflict emotional pain upon another (Lewis & Weigert, 1985). In the context of this research, a seller and an expert who work together frequently may develop both cognitive and affective trust.

**Types of Trust in the Seller/Expert Scenario**

We assume in this scenario that the seller has a go-to expert with whom they have worked previously. The seller and go-to expert have likely developed cognitive and affective trust through their past working relationship. Cognitive trust having been developed through repetitive demonstration of competence and affective trust potentially forming over time through a deepening of personal care.

Because maintaining a positive relationship with the customer is critical to the seller’s future sales, the seller may be concerned about introducing untrusted experts to the customer. To encourage sellers to select a technically-best-qualified but unknown expert for a given sales scenario, the seller needs to trust the unknown expert enough to be willing to be vulnerable to them. Thus, to facilitate the selection of the technically best expert, we need to support trust development.
Given that affective trust has an emotional element and takes time to develop, cognitive trust is the most likely target for building a connection between the seller and unknown expert (Johnson & Grayson, 2005; Lewis & Weigert, 1985). While cognitive trust is generally known to take time to develop, research has identified ways of quickly building cognitive trust. Those are addressed in the section titled “Strategies for Building Trust.”

In a scenario where a seller is deciding between engaging their go-to expert versus an unknown expert, we believe that relative trust levels will likely influence the outcome (Merritt, Sinha, Curran, & Ilgen, 2015). Consciously and perhaps unconsciously, the seller may compare the degree to which they trust their go-to expert with the degree to which they trust the unknown expert. The higher the seller’s initial levels of trust in their go-to-expert, the more difficult it becomes for our interventions to “overcome” that high level of trust. Thus, we propose that the seller’s initial trust levels in their go-to expert will significantly influence their expert selection decisions.

_Hypothesis 1 a and b: increased a) cognitive trust and b) affective trust in a known expert will predict the likelihood of engaging that expert relative to an unknown expert who has better technical expertise for the sales scenario._

_Preference for Known/Trusted Experts_

As described in practice, sellers often bring a known and trusted expert into a customer relationship, even if that individual has less technical capabilities than another available expert. This behavior has been documented empirically by Buntain and Golbeck (2015). In their study, participants played an investment game with a partner. Subsequently, they changed games to a modified (team-oriented) game of Battleship.
They could choose to continue playing with their current partner (from the investment game) or switch to a new partner with higher Battleship skills. Their participants overwhelmingly chose partners with whom they had previously developed trust over potential partners with higher documented scores in Battleship. The participants chose trusted partners over Battleship experts. The known partner is more convenient, trusted, and willing to help (Goodwin-Sak, 2019; Granovetter, 1983). This scenario parallels Cisco’s situation, where sellers typically engage their go-to expert instead of a more technically capable expert. This is the critical challenge in our study that we must overcome.

**Social Network Ties**

Social network theory also informs how trust builds between the seller and known experts, but not unknown experts. Social network ties can be characterized by their **strength**, conceptualized via the frequency of interaction, similarities between those connected, emotional intensity, and reciprocity (Granovetter, 1973; McPherson et al., 1992). If a seller has spent a great deal of time with a known technical expert, they are more likely to have a **strong network tie** and share some similarities (Granovetter, 1973). Granovetter suggests that the strong tie between the expert and the seller will make it more convenient for the seller to ask the expert for help, and the expert will have greater motivation to help the expert (1983). Further, social interaction between two individuals is an indicator or a precursor of trustworthiness (Tsai & Goshal, 1998). Assuming previous positive outcomes, a seller likely trusts the expert with whom they work the most because they have frequent interactions. As mentioned previously, trust is essential to a seller when introducing an expert to their customer.
The challenge with strong ties is that they limit knowledge sharing and diversity of knowledge. Granovetter’s (1973) research showed that individuals seeking jobs spent less time unemployed when they used weak ties to find job opportunities and provided a favorable recommendation. Through two different job-changer studies, he found that the highest percentage of respondents found their role from an individual defined as an acquaintance or someone the respondent only sees occasionally (Granovetter, 1973). Similar research has been done in seeking and sharing technical advice. Constant et al. (1996) found that when seeking experts to answer questions, expertise received through weak ties provided more useful information. They found that diversity rather than quantity of experts yielded the most helpful information. This is not to say that knowledge gained from experts with strong ties will be harmful. Instead, sellers should be encouraged to access experts through weak ties to get greater information or expertise (Levin et al., 2002).

A seller relying on a single expert or an expert with strong ties for all situations may encounter a unique technology or competitive environment where his/her go-to expert does not have enough technical skill to address the situation properly. In that case, rather than relying on their strong ties network, they would be better off leveraging a weak tie to get a greater diversity of knowledge. More substantial expertise may play a significant role in the sales process when competing against a narrowly focused competitor. The problem, of course, is that in many cases, no network tie exists at all between the seller and the best-qualified technical expert. Thus, one of the functions of the intervention we develop must establish a greater number of weak ties between sellers and (previously unknown) technical experts.
Swift Trust

Traditional trust-building theories assume that trust-building requires time and a series of behavioral interactions that meet expectations. McKnight et al. (1998) define this as knowledge-based trust. In contrast, some research suggests that we can quickly establish trust; this type of trust is termed swift trust. For example, when experimenting with trust via an investment game, Berg et al. (1995) found that participants displayed high initial trust in their previously-unknown partners. McKnight et al. (1998) propose that initial trust is associated with “an individual’s disposition to trust or on institutional cues that enable one person to trust another without firsthand knowledge” (p. 474). While the relationship of propensity to trust and initial trust has been well-established (McKnight et al., 2002), trait-like constructs such as propensity to trust provide the organization with little opportunity for intervention. For this reason, we assessed the propensity to trust in our experiment.

More promising from an intervention standpoint, research suggests that initial trust is also influenced by category-processing or ingroup identification (Robert et al., 2009). In other words, people are more likely to initially trust individuals whom they perceive as members of a group who share similar traits. Category processing is based on an individual's characteristics rather than behavior (McKnight et al., 1998). Categories include unit grouping with common goals and values, reputation, and stereotypes (McKnight et al., 1998). Initially, the seller likely has little knowledge of the unknown expert's goals and values, aside from the person’s membership in the “technical expert” category. We seek to find interventions that create swift trust between sellers and experts by leveraging the common ingroup identity model.
Social Identity Theory and Trust

A theory that informs potential interventions is Social Identity Theory, initially researched and defined by Tajfel (1972, as cited by Abrams & Hogg, 2006). Social Identity Theory is “the individual’s knowledge that [they] belong to certain social groups together with some emotional and value significance to [them] of the group membership” (Tajfel, 1972. as cited by Abrams & Hogg, Chapter 2 Introduction, 2006). Just as trust allows us to simplify decision-making, so does categorization and labeling with self-descriptions. Categorization simplifies perception (Abrams & Hogg, 2006). Without this heuristic function, humans would be paralyzed by decision analysis and unable to function. Instead, categorization fulfills a need for individuals to identify social order and structure predictably (Abrams & Hogg, 2006).

At the same time, individuals choose ingroups within which they belong socially and outgroups with which they do not belong. Finding similarities with an ingroup highlights the differences between groups (Tajfel, 1957; Tajfel,1959 as cited by Abrams & Hogg, 2006). The result of self-classification and categorization creates group prototypes (Abrams and Hogg, 2006). These group prototypes are stereotypes of an individual’s ingroup as well as outgroups.

The American media often portrays engineers and computer scientists in movies and television shows as socially unskilled or awkward and singularly focused on technology (Cheryan et al., 2015). Other labels for this description are “geeky” or “geeky know-it-alls” (Cheryan et al., 2015; Fisher & Margolis, 2002). American media perpetuates these stereotypes through television shows such as The Big Bang Theory and Silicon Valley. These shows portray engineers and computer scientists “as mostly
white…socially unskilled, and singularly obsessed with technology” (Cheryan et al., 2015, para. 15). Similarly, in interviews with sellers, they often cited experts’ poor ability to adapt to customer social queues and poor communication skills when discussing customer meetings that went poorly (Goodwin-Sak, 2019). This stereotype presents a categorization and risk we must overcome for the seller to develop trust with the expert.

**Defining the Ingroup and Outgroup**

While sellers and experts are members of the same technology company and likely members of the same organization, such as a sales organization, sellers and engineers have different roles in the organization and sales process. They often report to different managers, have different training, and are compensated differently. As such, these roles may lend themselves to ingroup identification (Ashforth & Mael, 1989).

As we identified that technical experts are already labeled with the stereotype of poor interpersonal skills, categorical thinking may trigger the seller to view the expert as 1) in the outgroup and 2) negatively stereotyped in terms of social skills (Akbulut-Bailey, 2013; Enns et al., 2006; Galetta, 2007). Any negative encounter between a seller and an expert at some point in the seller’s career may simply solidify and amplify the stereotype of the expert outgroup (Ramasubramanian, 2011; Cheryan et al., 2013).

As an outgroup member from the seller, and as mentioned above, the seller is likely to emphasize the negative traits of the outgroup or expert group. The mere existence of the word “expert” or “engineer” may create an unavoidable category activation of the expert's stereotype. Several research studies have tested the priming stimulus of labels and find that those labels' presence activates categorization (Dovidio & Gaertner, 1986; Macrae & Bodenhausen, 2000).
In prior research, sellers were asked to identify the most valued qualities in the experts they engaged. Technical expertise was typically last on the list of attributes seen as favorable by the seller (Goodwin-Sak, 2019). It is possible that sellers in this scenario simply assume technical competence among available experts. However, through a phenomenon labeled ingroup projection, sellers may project their own ingroup stereotype behaviors onto experts in the newly formed ingroup (Wenzel et al., 2007). Goodwin-Sak (2019) indicates sellers are looking for specific traits in experts, such as listening to the customer’s needs and adapting to address those needs in the conversation with the customer. We carry forward these concepts and design an intervention to reframe the ingroup to include both sellers and experts and to identify experts with the expected ingroup selling behaviors.

**Strategies for Trust Building**

This section reviews research informing the intervention's design to increase seller trust in the unknown but technically qualified experts. Luhmann and Niklas (2018) provide insight that we can influence trust with their statement that “[t]rust is not a means that can be chosen for particular ends, much less an ends/means structure capable of being optimized” (p. 97).

**Common Group Identity Model - Recategorization**

The Common Group Identity model offers us insights into how we might reframe individuals’ categories and groupings to broaden their categorization and reduce intergroup bias. Gaertner et al. (1993) found that it is possible to help individuals recategorize themselves to an inclusive “we” group that was previously two separate ingroups. Riek et al. (2010) applied this concept to politically divided students, finding
that using superordinate categories could expand the ingroup's categorization, increasing positive feelings between outgroups.

Experts and sellers frequently have common organizational attributes, such as reporting to a company's sales organization. This creates the potential for a superordinate group with which individuals within a group may identify. We’ll use the organization's name, identifying logos, colors, and phrases to create a common ingroup identity (Dovidio & Gaertner, 1986; Dovidio et al., 1997).

*Hypothesis 2 – Facilitating a superordinate ingroup identification to capitalize on common ingroup identification will increase:*

- a) trust in the chosen expert, and
- b) the likelihood of the seller choosing the unknown expert.

*Individuating Information*

As referenced in the literature review, our sellers' two significant areas of concern are technical expertise and interpersonal skills. According to sellers, both influence the likelihood of a “win” in a sales scenario (Goodwin-Sak, 2019). Thus, information about the technical expert’s previous success rate can be considered individuating information. In two experiments conducted by Krueger and Rothbart (1988), they found that behaviorally relevant individuating information is highly correlated to disregarding categorical stereotypes. While an expert’s win rate is influenced by other factors (including the seller's skills), an impressive win rate suggests that the technical expert’s technical and interpersonal skills are sufficient to secure the sale. Win rate information can be shared in an intervention as an additional rationale to give the seller confidence in the expert’s competence, thus accelerating a portion of cognitive trust.
Hypothesis 3: provision of (positive) individuating information will significantly increase:

a) trust in the chosen expert and

b) likelihood of the seller choosing the unknown expert.

Transfer of Trust

Sellers may initially view unknown experts as outgroup members because of their lack of network ties and individuating information. We look to additional interventions that have built trust between members of different groups. Two prominent studies explored trust connections outside of an organization. Strub and Priest (1976) studied the patterns of marijuana users, which at the time was a high-risk behavior, to understand how they identify other marijuana users. The authors identified a fascinating pattern where if User A trusts User B, and User B trusts User C, User A will trust User C (when User B identifies his/her trust in User C). This presents an opportunity to leverage affinity groups to help us “transfer trust” in an expert from one seller to another.

Using McKnight and others' trust work, Stewart explored the ability to transfer trust relationships from one source to another on the World Wide Web. This research concluded that a human trust relationship could be transferred to trust in unknown entities on the World Wide Web (Stewart, 2003; McKnight, 1998).

McKnight (1998) distinguishes between trusting beliefs (general attitudes toward trust) and trusting intentions (plan to take action in a specific situation). Trusting intentions in a particular situation require the trustor to make themselves vulnerable to the trustee. The trustor in our scenario is the seller. The trustee is the expert.
If no connection exists between the seller and the expert, a third-party broker may act as a mediator, transferring their trust in the expert to the seller (Stewart, 2006; Wang, Shen, & Sun, 2013). Trust transfer is a cognitive process where the trustor “bases initial trust in an entity” (the unknown expert) “on trust in some other related entity” (Stewart, 2003, p. 6). In the Strub and Priest (1976) study, they describe the process of transferring trust as the third party providing a measure of trustworthiness of the unknown party. The trustor then accepts or rejects the third party’s opinion (Stewart, 2006). In this and other scenarios, transfer of trust requires that the trustee has some relationship with the third-party broker (Stewart, 2006). Additionally, Stewart (2006) suggests that evidence of ties between groups increased the perception of similarity. However, the presence of multiple ties creates lower perceived similarity than the presence of a single tie (Stewart, 2006).

In our case, the third-party broker is another seller in the same organization (an ingroup member), and precisely, one that our seller respects. Knowledge of previous interactions between the unknown expert and the third-party broker is likely to increase perceptions of entitativity (or perceptions of belonging to the ingroup) between the unknown expert and the sellers as a group, thus transferring trust to the unknown expert. The third-party broker may also shape the expert’s reputation, allowing the trustor to develop swift trust for the expert. Trust transfer presents an opportunity in our scenario to leverage the relationships of others to accelerate the trust development between a seller and an expert.
Hypothesis 4: positive recommendations from a respected seller will capitalize on entitativity to transfer trust and will significantly increase:

a) trust in the chosen expert and

b) likelihood of the seller choosing the unknown expert.

Summary

The key obstacle in bringing an unknown expert into a sales opportunity is the risk associated with a seller’s lack of sufficient experience with an unknown expert to anticipate their behavior in the sales opportunity. The seller lacks cognitive trust in the unknown expert, particularly regarding interpersonal skills, which are negatively stereotyped among technical experts. We sought to use several interventions to build swift trust between the seller and the expert. Those interventions included:

- Establishing network ties between sellers and unknown experts
- Transferring trust via social ties (“recommendation”)
- Conveying information about the expert’s social and technical skills to demonstrate competency, a key component of cognitive trust (“individuating information”)
- Helping sellers view experts as a member of their ingroup through superordinate categorization (“common ingroup")

The intended result of these interventions was that sellers would experience increased trust in the unknown expert and choose to engage the unknown expert in risky situations.
Chapter 3: Methods and Measures

Research Design / Methodologies

To avoid potential negative financial impact on sellers and their relationships with their experts, we chose to leverage a quantitative vignette study for this research. Vignettes are often used for studies where direct experimentation may present untenable ethical challenges (Nosanchuk, 1972). The vignette allows for the construction of scenarios to create context and systematically manipulate multiple independent variables for which the respondent makes choices. This vignette study presented a series of scenarios to the respondent, manipulated our independent variables, and measured the respondent’s level of trust and likelihood of engaging the unknown expert in each scenario (Steiner et al., 2016).

To adequately reflect the real-world context of interest, each vignette presented a relatively risky sales scenario (offering a financially large deal in the range of the seller’s usual deals). Furthermore, in every case, the unknown expert had better technical qualifications than the go-to expert for the product being pitched. Other elements were manipulated either across scenarios or between persons, as discussed further below. For each scenario, the participant chose between the known and unknown experts for the scenario, then provided feedback on their choice. The objective was to identify interventions that build sufficient swift trust between the seller and the unknown expert to allow the seller to choose the unknown expert for the customer meeting scenario.

Internal Validity

The design of a vignette is critical to its internal validity. Many factors can impact the internal validity of the vignette. First, vignettes are most effective when they resonate
with the participants and appear realistic or psychologically similar to their actual experiences. In these circumstances, participants are more likely to respond authentically, increasing the data's quality (Hughes & Huby, 2004). Similarly, you don’t want to lose the participant's interest, so vignettes should not be too long (Hughes & Huby, 2004).

To create a realistic environment for the seller, we asked the seller to give information about the typical size of their customer accounts and the average amount of a “large” sales deal (in dollars). This information allowed for the creation of a personalized “high” risk level for the seller. Finally, we asked the seller for their go-to expert's initials to refer to the actual expert. These steps created a sense of realism.

Secondly, vignettes' serialization can result in “carry-over” impacts in responses (Sniderman & Groub, 1996). To prevent serialization, the questions were designed to prevent a cumulative effect on subsequent scenarios. We accomplished this by randomizing the intervention conditions. Participants were told that they should consider each scenario independently and would be given no feedback on the “success” of the outcome. Additionally, there were no rewards for any specific choices and no choice within the vignettes that impacted future choices or the payout. Finally, because of the potential carry-over influences of the common ingroup manipulation, this manipulation was performed between-persons. The manipulation is designed to change the perceiver’s frame of reference; therefore, we expected that it would have carry-over effects to subsequent scenarios if manipulated within-persons.

Finally, building on the literature reviews, pre-testing the survey and expert review can increase the vignette's validity (Flaskerud, 1979). We conducted a pilot test with a sample of sellers in Australia. The seller role in the company and organizational
constructs between the United States and Australia are very similar. Additionally, research shows that managers have a very similar ideology in these countries, leading to similar work priorities and individual traits (Westwood & Posner, 1997). Sellers were asked to participate in a subset of the study and were asked for feedback on the study's length, the realistic nature of the scenarios, and any concerns over understanding the questions. Any issues with clarity or other functional problems were documented and remedied before implementing the full study in the United States.

Sample

Participants were selected from a database of sellers at Cisco, all located in the United States. The minimum requirement for eligibility to participate was employment with the company in a sales role for at least one year. There was no restriction on demographics other than being a seller of the company’s technology equipment to other entities in the United States. The individuals had a title similar to Account Manager or Client Executive.

Recruitment

For recruiting purposes, names of qualifying potential participants were collected from the company’s goal sheet database. Participation in both the pilot and full study was solicited via email over two weeks. The pilot study leveraged an anonymous email distribution system available via Qualtrics. That system allowed for unique survey links to be sent to each participant with reminder emails but also preserved the anonymity of the participant responses. The emails generated from the Qualtrics system were sent to the participants’ “Spam” folder in their email application. There was zero response from the pilot study group. The researcher created an anonymous link and shared it with one of
the managers in Australia but was not directly responsible for any of the participants. That manager encouraged participation. We received six total responses in the pilot study.

Challenges in attaining responses from the first study required us to reassess the incentives offered to the participants. The targeted participants were highly paid individuals with very little spare time. The initial incentive was a gift card provided in the context of “a small token of appreciation.” Based on the very limited response to the pilot study, we redesigned the incentive structure to include a raffle for eight prizes. Participants were given five prizes from which to choose. Four prizes were tangible items to be shipped to them. The fifth prize was a $300 donation to a charity of their choosing. If their charity was available on the corporate giving site, the corporation would match that donation for a total of $600 to the charity. Upon completion of the survey, participants were presented with the opportunity to share an email address. After the survey closed, eight participants were randomly chosen using the “randbetween” function in Microsoft Excel. They were contacted and given the option of choosing a prize and sharing a mailing address. All eight items were shipped, and a note was sent to all who shared their email addresses that the raffle was complete and expressing gratitude.

Participants

Emails were sent to 701 sellers in the United States. A total of 130 responses, of which 92 were complete, were collected over a two-week period. The demographics for the sample are in Table 3.1.
Table 3.1

*Demographics of the Original Sample Participants*

<table>
<thead>
<tr>
<th>Category</th>
<th>Number</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>65</td>
<td>70.7%</td>
</tr>
<tr>
<td>Female</td>
<td>27</td>
<td>29.3%</td>
</tr>
<tr>
<td>Race and Ethnicity</td>
<td></td>
<td></td>
</tr>
<tr>
<td>White</td>
<td>79</td>
<td>85.87%</td>
</tr>
<tr>
<td>Black or African American</td>
<td>4</td>
<td>4.35%</td>
</tr>
<tr>
<td>Asian American</td>
<td>2</td>
<td>2.17%</td>
</tr>
<tr>
<td>Native Hawaiian or Pacific Islander</td>
<td>1</td>
<td>1.09%</td>
</tr>
<tr>
<td>Other</td>
<td>6</td>
<td>6.52%</td>
</tr>
<tr>
<td>Age</td>
<td></td>
<td></td>
</tr>
<tr>
<td>20-30</td>
<td>16</td>
<td>17.39%</td>
</tr>
<tr>
<td>31-40</td>
<td>26</td>
<td>28.26%</td>
</tr>
<tr>
<td>41-50</td>
<td>28</td>
<td>30.43%</td>
</tr>
<tr>
<td>51+</td>
<td>22</td>
<td>24.91%</td>
</tr>
<tr>
<td>Experience</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Years in Sales at Company</td>
<td>7.38</td>
<td>6.72</td>
</tr>
<tr>
<td>Total Years in Tech Sales</td>
<td>14.82</td>
<td>9.76</td>
</tr>
<tr>
<td>Additional Measures</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Role/Title Account Manager</td>
<td>92 (100%)</td>
<td></td>
</tr>
<tr>
<td>Ingroup treatment</td>
<td>55 (59.8%)</td>
<td></td>
</tr>
</tbody>
</table>

**Procedure**

This experiment (Figure 3.1) was a 2 (individuating information: present, absent) x 3 (social network recommendation source: respected, unknown, none) x 2 (common ingroup identity: present, absent) factorial design. Individuating information and social network were manipulated at the vignette level, such that each participant received some vignettes with and without these elements. Because common-ingroup manipulation is hypothesized to change the participant’s overall frame of reference toward technical
experts, we expected that it could affect their behavior on all subsequent vignettes once participants see it. Therefore, a common ingroup identity was manipulated between-persons.

All procedures were reviewed and approved by the UMSL IRB before recruiting participants. Participants signed a consent form (Appendix B). Next, participants were presented with a series of demographic information questions, including gender, age, company sales tenure, technical sales tenure, title/role. Making vignettes appear realistic maximizes the accuracy of the participants' information (Hughes & Huby, 2004). To make the risk environment as realistic as possible, participants answered a series of questions about their customer's business sector, customer’s size, and large deal size for the seller. We used their responses to these questions to personalize the “deal size” information in their vignettes.
The participant was asked to provide the initials of their go-to expert for most of their sales opportunities so that we could refer to this person in the vignettes. The seller ranked the expert’s technical capabilities in five technology areas, from strongest to weakest. We also asked the seller to provide the first name of another seller (an individual in the same job role that they occupy) whom they respect for their sales skills. This information was used as a part of the social network manipulation.

**Vignette**

For trust to be present, risk must be present (Mayer et al., 1995). There are three ways we created risk for the seller, and those elements were present for all participants to produce comparable levels of risk across participants. First, we indicated that the customer relationship is not fully developed or there was a factor that puts the relationship at risk. Secondly, using the information each seller provided us about the dollar value of a large sale, we created risk by presenting a similar-sized sales
opportunity to the seller. By taking the participant’s input on the value of a “large” deal and varying the simulated opportunity size by - 3%, we create a realistically large sales deal that was not identical to their entry. Thirdly, we created vignettes where the sales opportunity was in the weakest technology areas for the seller’s go-to expert, simulating an environment where there is a more skilled expert for the opportunity.

**Vignette Terminology**

While the terminology in this research refers to technical experts, the company's terminology refers to their technical experts as “engineers” or “pre-sales engineers.” The scenarios in our vignettes included this terminology. Sellers in the organization also refer to their sales deals as “opportunities.” We used that language in the vignette to preserve realism. Additionally, in prior research (Goodwin-Sak, 2019), sellers insisted that they would not bring an unknown engineer into a customer meeting without first having a preparation call. In almost every instance, this was a non-negotiable condition for the seller. It provides the seller with information on the expert's technical and social ability and an opportunity to strategize on areas of customer interest. We indicated to the seller in every scenario that there is an opportunity to meet with any expert chosen before the meeting with the customer.

**Control Vignettes**

The first two vignettes included no manipulations and confirmed sellers’ tendencies to default to their go-to-expert. In the first scenario, the seller was presented with customer relationship risk and a large opportunity *in the go-to expert's area of expertise* (go-to expert more technically qualified than unknown expert). We expected that sellers would almost universally choose the go-to-expert over the unknown expert in
this control scenario. Thus, the scenario checked that participants correctly understood the vignette task and provided one form of attention check.

The second control vignette paralleled the first except that, in this case, the product was in the go-to expert's worst-ranked technology (unknown expert more technically qualified than go-to expert). This allowed us to establish a base rate of the extent sellers tend to default to their go-to-expert, even when less technically qualified. Thus, we could examine the extent to which each manipulation produced changes compared to this control scenario.

*Control 1:*

You have a customer opportunity in [go-to expert’s #1 ranked technology]. This opportunity's potential dollar amount is [ - 3% seller’s large opportunity].

Your meeting is with a new technology director in the customer’s company. You have only met with this individual twice previously and have not yet built a strong sales/customer relationship with them. You strongly suspect a competitor is attempting to gain your customer’s attention.

You can only choose one pre-sales engineer to take with you to the customer meeting, but you have the opportunity for a preparation session with any expert you choose before visiting with the customer.

Our database search found another available engineer with expertise matching this opportunity.

*Please review this information carefully* and answer the questions below. **Reminder**, you have the opportunity for a prep meeting with any expert you choose.
Which engineer would you select to take to the meeting? Reminder, you have the opportunity for a prep session with any expert you choose.

☐ This engineer (name withheld for research privacy)

☐ Go-to Expert (provided by participant)

Control 2:

You have a customer opportunity in [go-to expert’s worst-ranked technology]. This opportunity’s potential dollar amount is [− 3% seller’s large opportunity].

Your meeting is with a new technology director in the customer’s company. You have only met with this individual twice previously and have not yet built a strong sales/customer relationship with them. You strongly suspect a competitor is attempting to gain your customer’s attention. You have the opportunity to choose an engineer to take to the meeting with you. Regardless of your choice of engineer, you have the opportunity for a prep meeting before the meeting with the customer.

Our database search found another available engineer with expertise matching this opportunity.
Please review this information carefully and answer the questions below. Reminder, you have the opportunity for a prep meeting with any expert you choose.

Which engineer would you select to take to the meeting? Reminder, you have the opportunity for a prep session with any expert you choose.

- [ ] This engineer (name withheld for research privacy)
- [ ] Go-to Expert (provided by participant)

**Experimental Manipulations**

*Manipulation 1 – Individuating Information: Present vs. Absent*

The presence or absence of individuating information was manipulated within-subjects at the scenario level. When individuating information was presented in the form of the previous “win rate.” In the organization’s language, the win rate refers to the percentage of sales opportunities that the sales team documented in which the expert was involved where the customer’s business was secured. The win rate likely reflects on both the expert’s technical competence and social skills. Given previous data collections indicated that sellers primarily held negative stereotypes about technical experts’ social skills (Akbulut-Bailey, 2013; Enns, Ferratt, & Prasad, 2006; Galetta, 2007), a reasonable win rate indicates that the expert possesses sufficient social skills to make a sale.
When providing information about individuals and their success rates, we standardized the differences between expertise levels. We are primarily concerned with situations where a seller rejects an expert who is more highly qualified in the sales pitch’s particular technical area. In our scenario, there was no reason to propose a different expert to take to the customer unless we identified an expert with a higher success rate. When individuating information is present, our unknown expert has a high success rate in an area of lowest expertise for the go-to expert. This and all subsequent manipulations use the same scenario as our Control 2, with risk present. See Figure 3.2 for an example.

**Figure 3.2**

*Individuating Information Present*

<table>
<thead>
<tr>
<th>Search results for: Data Center</th>
</tr>
</thead>
<tbody>
<tr>
<td>S. T. R. (initials used for privacy)</td>
</tr>
<tr>
<td>Primary Expertise: Data Center</td>
</tr>
<tr>
<td>Win Rate = 85%</td>
</tr>
</tbody>
</table>

**Manipulation 2 – Recommendation Source: Respected vs. Unknown vs. Unnamed**

To study the effects of a positive recommendation of another seller, we assessed the effects of the presence and source of a positive recommendation for the unknown expert. Recall that at the beginning of the study, we asked each participant to provide us with identity pseudonyms for another seller whom they respect. In the “respected source” condition, the unknown expert received a positive recommendation from one of these respected sellers (Figure 3.3). In the “unknown” source condition, the unknown expert received a positive recommendation from an unknown seller (Figure 3.4). In the
“unnamed” condition, a name was absent, but the participant was labeled as “recommended” (Figure 3.5).

**Figure 3.3**

*Respected Seller*

![Search results for: Data Center](image)

S. M. R. (initials used for privacy)

Primary Expertise: Data Center

👍 Recommended by Joe

**Figure 3.4**

*Unknown Seller*

![Search results for: Data Center](image)

J. M. S. (initials used for privacy)

Primary Expertise: Data Center

👍 Recommended by Gerald Smith

**Figure 3.5**

*Unnamed Recommendation*

![Search results for: Data Center](image)

S. J. T. (initials used for privacy)

Primary Expertise: Data Center

👍 Recommended
Manipulation 3 – Common Ingroup: Present or Absent

For this manipulation, we attempted to reframe participants’ salient categorization from the category of “technical expert,” which is associated with negative stereotypes, to “Cisco sales organization” -- an overarching category in which the participant and the expert share ingroup membership. This manipulation was between-persons.

This manipulation leveraged the common ingroup identifier of Cisco (company membership). In the common ingroup identity condition, all vignettes included the Cisco logo to each vignette expert profile, and the avatar was wearing a Cisco-branded polo-style shirt. In this condition, the vignettes also featured the Cisco color scheme and the Cisco employee social media slogan, “#WeAreCisco.” The Cisco logo and slogan were removed in the control condition, and the color scheme was black, white, and grey (Dovidio & Gaertner, 1986; Dovidio et al., 1997). See Figure 3.6 as an example of the ingroup manipulation.

Figure 3.6

Common Ingroup

Self-Report Measures

Following the vignettes, we measured some self-report variables for use in our hypothesis testing (cognitive and affective trust the seller has for their go-to expert) and
potential supplemental analyses (e.g., propensity to trust). Finally, we moved the participant to a separate survey to collect their contact information for the participation incentives.

**Measures**

**Demographics**

Participants were asked to specify their gender, race, age, title, tenure within Cisco sales, and years in technical sales.

- **What is your gender?**
  - ⭕ Male
  - ⭕ Female
  - ⭕ Other

- **What is your race?**
  - ⭕ White
  - ⭕ Black or African American
  - ⭕ American Indian or Alaska Native
  - ⭕ Native Hawaiian or Pacific Islander
  - ⭕ Other

- **What is your age?**
  - ⭕ 20-30
  - ⭕ 31-40
  - ⭕ 41-50
  - ⭕ 51+

Years in sales at Cisco and overall years in technical sales were measured on a sliding scale, as seen in Figure 3.7.
Business Sector and Customer Size

Participants were asked what sector of the business they cover: private companies, public sector organizations, or service providers. Additionally, they were asked which tier they align to (a corporate account size classification). We also asked participants to provide the size of a relatively large opportunity, which was used to establish a relatively large risk level in the vignettes.

What sector of the business do you cover?

- Private Companies
- Public Sector Organizations
- Service Providers

What tier of customer business do you cover?

- Premier / Key
- Major / Select
- Mid-Sized

Go-to Expert and Seller Details

To personalize the vignette, sellers were asked to provide information on their go-to expert. To protect the identity of the expert, the specific question asked was:
What are the initials or nickname of your go-to engineer? (to protect privacy) This is the engineer you normally work with or prefer to work with. If you have more than one, choose the one you most often work with.

Nickname / Initials – your Go-To Engineer:

To appropriately address the risk in a scenario, we asked the seller to rank the go-to expert’s competencies. The technologies were presented in random order in the surveys. In all scenarios (other than the control), the unknown expert was presented as having expertise better suited to the opportunity’s needs than the go-to-expert.

Rank your engineer’s expertise from 1 (Greatest Expertise) to 4 (Least Expertise). You cannot select the same number twice.

<table>
<thead>
<tr>
<th>Enterprise Networking / Wireless</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>🟩</td>
<td>🟩</td>
<td>🟩</td>
<td>🟩</td>
</tr>
<tr>
<td>Security</td>
<td>🟩</td>
<td>🟩</td>
<td>🟩</td>
<td>🟩</td>
</tr>
<tr>
<td>Collaboration</td>
<td>🟩</td>
<td>🟩</td>
<td>🟩</td>
<td>🟩</td>
</tr>
<tr>
<td>Data Center</td>
<td>🟩</td>
<td>🟩</td>
<td>🟩</td>
<td>🟩</td>
</tr>
</tbody>
</table>

To properly establish the transfer of trust and acquisition of expertise through a social network, we ask the seller for the first name of another seller whom they admire or trust:

Share the first name of a seller at Cisco who you trust or whose sales skills you admire. We will only use this information later in the survey.

First Name- Respected Sales Peer:

Finally, to appropriately size the seller's risk, we asked for the average dollar amount of a large opportunity in their customer segment. See Figure 3.8 for an example.
Vignette Data Collection

Expert Choice (Dichotomous):

Participants chose an expert to take to the customer meeting:

Which engineer would you select to take to the meeting? Reminder, you have the opportunity for a prep session with any expert you choose.

- This engineer (name withheld for research privacy)
- Go-to Expert (provided by participant)

After that choice, we measured the seller’s expectations of the expert’s competence and social adaptability in each expert presented for the situation. Referring back to our Whitener et al.’s (1998) definition of trust that we’re leveraging for this research, in addition to the many definitions of trust in Table 2.1 (Chapter 2), we measure the seller’s expectation of the performance of each expert in the scenario. We use the term “expectation” specifically instead of “trust.” If the seller has developed affective trust for the go-to expert, the seller may not be comfortable indicating that they trust the unknown expert more than their go-to expert in a situation. It could be an indicator of disloyalty and negatively impact the responses to our continuous variables – a measure of trust (Johnson & Grayson, 2005). The items are measured with a five-point Likert-type scale with 1 correlating with “Strongly Disagree” and 5 correlating with “Strongly Agree.” The scale has three items:
Considering the information presented about the engineer found in the search results, please indicate the extent you agree with each of the following statements:

1. I expect this engineer would demonstrate technical expertise in this sales meeting.
2. I expect this engineer would adapt to the social cues of the customer.
3. I worry this engineer might make poor impression socially.

**Post-Scenario Questions**

All questions posed post-scenario were presented in the original order as designed. They were also given together to ensure the results' integrity and make the survey more straightforward for the participant to understand.

**Seller’s Affective and Cognitive Trust for Known Expert**

Affective and cognitive trust were measured by McAllister’s (1995) two-factor interpersonal trust scale. Respective reliability estimates for affect- and cognition-based trust are .89 and .91. The scales' items are measured with a seven-point Likert-type scale with 1 correlating with “Strongly Disagree” and 7 correlating with “Strongly Agree.” McAllister’s (1995) affective trust scale has five items:

1. We have a sharing relationship. We can both freely share our ideas, feelings, and hopes.
2. I can talk freely to this individual about difficulties I am having at work and know that they will want to listen.
3. We would both feel a sense of loss if one of us was transferred and we could no longer work together.
4. If I shared my problems with this person, I know they would respond constructively and caringly.
5. I would have to say that we have both made considerable emotional investments in our working relationship.

McAllister’s (1995) Cognition-based trust scale includes six items:

1. This person approaches their job with professionalism and dedication.
2. Given this person's track record, I see no reason to doubt their competence and preparation for the job.
3. I can rely on this person not to make my job more difficult by careless work.
4. Most people, even those who aren't close friends of this individual, trust and respect them as a coworker.
5. Other work associates of mine who must interact with this individual consider them to be trustworthy.
6. If people knew more about this individual and their background, they would be more concerned and monitor his/her performance more closely. (reverse coded)

We measure disposition to trust with Frazier et al.’s (2013) four-item scale.

**Seller’s Propensity to Trust**

We measured propensity to trust with Frazier et al.’s (2013) four-item propensity to trust scale. The scale leverages items from previous research and scale development and assesses validity in two studies compared to previously developed models (Goldberg et al., 2006; Huff & Kelley, 2003; Lee & Turban, 2001; Mayer & Davis, 1999; McKnight et al., 2002). The four-item trust scale demonstrated reliability in both studies, with $\alpha = .89$ in the first study (labeled study 3) and $\alpha = .88$ in the second (labeled study 4). The scales’ items are measured with a five-point
Likert-type scale with 1 correlating with “Strongly Disagree” and 5 correlating with “Strongly Agree.”

1. I usually trust people until they give me a reason not to trust them.
2. Trusting another person is not difficult for me.
3. My typical approach is to trust new acquaintances until they prove I should not trust them.
4. My tendency to trust others is high.

**Supplemental Measures**

When measuring choice in an organization that impacts seller relationships with their coworkers, we may wish to understand the sense of obligation that the seller feels for their coworkers. This is also described as normative commitment. Meyer and Allen (1991) created a three-component scale for measuring organizational commitment. Those three components are affective, continuance, and normative commitment. Widely used in studies on organizational commitment (15,892 citations of the 1991 paper on Google Scholar and 8,940 citations of the 1993 article as of the date of this paper), the primary concern with this scale is the strong correlation between affective commitment and normative commitment (Meyer et al., 1993).

We leveraged Meyer et al.’s 1993 scale modification of 6 items (α = .73) to understand the seller’s normative commitment (or sense of obligation) to their coworkers and how that may influence experts' choice. As we used only one factor of the three-factor model, the correlation between the two factors was removed. The scale was adapted to change the organization's foci to the coworker and reworded to indicate the coworker as the commitment target. The scales' items are measured with a five-point
Likert-type scale with 1 correlating with “Strongly Disagree” and 5 correlating with “Strongly Agree.”

1. Even if it were to my advantage, I do not feel it would be right to leave my coworkers.
2. It would not be morally right for me to leave my coworkers now.
3. If I got another offer for a better job elsewhere, I would not feel it was right to leave my coworkers.
4. I feel a personal responsibility to continue working for my coworkers.
5. I would feel guilty if I left my coworkers now.
6. I do not feel any obligation to remain with my current coworkers. (reverse coded)

Using Akbulut-Bailey’s (2009) instrument for understanding student stereotypes of IS professionals, we assessed the participants of experts in their organization as “geeks” using a three-item, seven-point Likert-type scale ($\alpha = .818$). The scales’ items are measured with a seven-point Likert-type scale with 1 correlating with “Strongly Disagree” and 7 correlating with “Strongly Agree.” We have modified the subject of the items to align with the specific role grouping within the company.

1. Systems Engineers tend to be nerds
2. Systems Engineers tend to be technology geeks
3. When I think about Systems Engineers, I think about computer geeks.

Given that trust depends on the presence of risk in a given situation (Giffin, 1968; Whitener et al., 1998), there was a potential need to control for an individual’s risk tolerance. The Survey of Consumer Finances (SCF) has included a single item question since 1983 (Yao et al., 1993). While many studies have examined the validity and have
found that the item does not represent the entire view of a consumer’s risk tolerance, it is still used in many studies to gauge the risk-taking preferences of study participants against the general risk-taking preferences of the American population (Grable & Schumm, 2010). Because the survey is delivered electronically, among other questions, we have removed the phrase “on this page” from the item used in the SCF.

Which of the following statements comes closest to the amount of financial risk that you are willing to take when you save or make investments?

1. Take substantial financial risk expecting to earn substantial returns.
2. Take above-average financial risks expecting to earn above-average returns.
3. Take average financial risks expecting to earn average returns.
4. Not willing to take any financial risks.

Finally, we presented an open-ended question to the participants asking them for information on what qualities they seek when engaging an expert for a customer meeting.

What are your main points of consideration when selecting an expert to attend a customer meeting?

_Hypotheses Testing_

Our study included within-subjects and between-subjects tests. Each participant viewed two control vignettes and six experimental vignettes. Our Level 1 outcomes included trust (particularly trust in the expert’s social capabilities) and expert choice. Level 1 predictors included individuating information, recommendation source, and potentially additional controls. Level 2 predictors included the common ingroup identity manipulation and, potentially, additional controls. Hierarchical linear modeling allows us to account for the nested data structure in calculating standard errors and variance. We used the hierarchical linear modeling package _lme4_ in R.

Before conducting hypothesis tests, we computed the null (intercepts-only) models for each outcome variable. These models allow the average level of the dependent
variable to differ across participants but include no predictors. The null model produces
an intraclass correlation coefficient (ICC) estimate to gauge the variance of the dependent
variable within-person and between-person levels. An ICC of approximately .05 or
higher supports the need for hierarchical linear modeling (LeBreton & Senter, 2008).

Hypothesis 1a and 1b are observations of choice as influenced by cognitive and
affective trust in the go-to expert. The logistic HLM equation for Hypotheses 1a and 1b
is:

\[
\text{Choice}_{ij} = Y_{00} + \beta_{01} \times (\text{CognitiveTrust}_j) + \beta_{02} \times (\text{AffectiveTrust}_j) + \mu_j + e_i
\]

Hypothesis 1a is supported if \(Y_{01}\) is positive and significant. Hypothesis 1b is
supported if \(Y_{02}\) is positive and significant.

Hypotheses 2a, 3a, and 4a all are a measure of trust under different conditions.
Two of the conditions, individuating information: presence, absence; and
Recommendation: Respected, Unknown, Absent are level 1 variables.

Level 1 model is constructed as such:

\[
\gamma_{ij} = \text{Trust\_Chosen\_Expert}
\]

\[
\gamma_{ij} = \beta_{0ij} + \beta_{1ij} \times (\text{IndividInfo}_{ij}) + \beta_{2ij} \times (\text{Recommend\_Respect}) + e_{ij}
\]

The InGroup treatment (present, absent) is a between-subjects or level 2 variable.

The Level 2 model is constructed as such:

\[
\beta_{0j} = Y_{00} + \gamma_{01} \times (\text{InGroup}_j) + \mu_j
\]

Hypothesis 2a (common ingroup) is supported if \(\gamma_{01}\) is positive and significant.

Hypothesis 3a (individuating information) is supported if \(\beta_1\) is positive and
significant. Hypothesis 4a (respected recommendation) is supported if \(\beta_2\) is positive
and significant.
Hypotheses 2b, 3b, and 4b are all dichotomous measures of choice. These hypotheses were tested using a generalized multilevel model with a binomial link function.

Level 1 model is constructed as such:

\[ \gamma_{ij} = \text{Choice}(0=\text{Go-To Expert}) \]
\[ \gamma_{ij} = \beta_{0j} + \beta_{1j} \times (\text{IndividInfo}_{ij}) + \beta_{2j} \times (\text{RecommendRespect}_{ij}) + e_{ij} \]

Level 2 model is constructed as such:

\[ \beta_{0j} = Y_{00} + \gamma_{01} \times (\text{InGroup}_i) + \mu_j \]

Hypothesis 2b (common ingroup manipulation) is supported if \( \gamma_{01} \) is positive and significant. Hypothesis 3b (individuating info) is supported if \( \beta_1 \) is positive and significant. Hypothesis 4b (respected recommendation) is supported if \( \beta_2 \) is positive and significant.

**Data Management**

An original copy of raw data was encrypted and stored in a cloud environment. The only user access to the original data is available to the principal investigator, requiring two-factor authentication. A secondary copy of the original data was altered to obscure any information provided by the participant that could determine their identity or that of individuals to whom they refer in the study. This is the data set that was analyzed for results.

**Ethical Considerations**

The email soliciting participation was from an executive in the company, but the individuals in the survey did not report directly to that executive. The email did not include the executive’s title but did come from that executive’s company email address.
Vignettes were used to simulate environments of risk without negatively impacting relationships with others in the workplace and to prevent any negative impact on their compensation. We issued a reminder statement before collecting information for participation rewards that all efforts will be taken to ensure the participants' data privacy and anonymity. This was to reassure the participant that their identity was not tied to their responses and there was no mechanism for doing so.

**Summary**

The study sought to identify interventions to establish seller trust in unknown technical experts and assess the extent to which sellers subsequently report a willingness to engage the best technical experts for their customer meetings to improve the chances of winning a sales opportunity. It was constructed to create a realistic simulation of a risky situation with minimal impact on any relationships for the participants or their experts.
Chapter 4 – Results

The focus of this study was on using interventions to overcome established trust relationships when an alternate expert is better for the organization. The study's primary research question was: can an intervention of data, trust transference, ingroup identity, or a combination influence the choice of expert a salesperson engages for a customer meeting?

Data Screening and Cleaning

The original 92 responses were screened for incomplete or missing data. Participants were required to answer each question, so no information was incomplete or missing. We assessed data quality using a combination of metrics including attention and manipulation checks and analyses designed to detect “insufficient effort responding” on a series of self-reported items. We created “flags” indicating potentially problematic responses on each of these metrics. Rather than relying on a single metric (each metric has unique limitations), we identified participants who were flagged on at least two metrics for initial exclusion from the dataset. The metrics were as follows.

Attention Checks

The study contained two attention check items (e.g., “for this question, please select “strongly agree”). We created flags indicating incorrect responses for each of the attention checks. Twelve individuals failed at least one attention check, and two individuals failed both of the attention checks.

The survey asked participants for the number of years in sales at the company as well as their total number of years in sales. Three individuals responded with fewer total years in sales than at the company. Each of these responses, 22, 41, and 63, were flagged.
Next, we conducted several analyses designed to identify cases of “careless” or “insufficient effort” responding. Insufficient effort responding can take several forms, and different metrics are used to identify each form (Huang et al., 2012). We conducted these analyses using the “careless” package within R (Dunn et al., 2018). This package for R calculates long-string and intra-individual response variability.

Long string responding refers to participants choosing the same response option repeatedly regardless of item content. We tested the supplemental measures for long string responses and found no continuous string of responses greater than three standard deviations. We tested the trust measures in the vignettes without recoding the third question (reverse coded) and found two outliers greater than three standard deviations from the mean. These were responses 86 and 90. Both were flagged.

Intra-individual Response Variability (IRV) can detect patterns of careless responses not detected by the long string function. Using this function from the “careless” package, we tested supplemental measures as well as the trust responses in the vignettes. There were no responses that exceeded three standard deviations from the mean.

In total, there were 19 careless responding flags. Because four individuals failed both at least one attention check and one additional potentially “careless” measure, we chose to remove those four responses from the sample, leaving 86 responses. See Table 4.1 below for details on respondents and the corresponding assessment failures.
Once we completed the first screening of the sample, removing careless responses, we calculated the smaller sample's (n = 88) descriptive statistics looking for unacceptable levels of skewness or kurtosis for each variable using standardized values.

The study is focused on overcoming an existing trust relationship through intervention to affect choice in an expert, so we assume an initially strong level of trust in the expert. We examined the responses for the trust measures to assess whether that assumption was met in all responses, and although mean trust levels were high, we identified a few cases that were outliers. The z-score for respondent 19 was greater than five standard deviations below the mean for cognitive trust in the go-to-expert, potentially indicating a lack of trust in that expert. The z-scores for respondents 9, 62, and 82 were all greater than three standard deviations below the mean for affective trust,
again indicating a lack of trust in the go-to-expert. Because these four responses violated the underlying conditions of the study and were significant outliers, we chose to remove them from the study sample. This left us with a sample of n = 84.

After recalculating the descriptive statistics and standardized variables for our sample, there were three new outliers. The standardized responses for respondents 20 and 64 were greater than three standard deviations from the mean of affective trust, and the standardized result of cognitive trust exceeded three standard deviations from the mean for respondent 86. Referring to Table 4.1, Careless Check Flags, we found that respondents 64 and 86 both had careless responses, but respondent 20 did not. We removed responses 64 and 86 but did not remove response 20 from our sample, leaving a final sample of n = 82. See Table 4.2 for the final data set’s demographics.
Table 4.2

*Demographics of the Final Sample Participants*

<table>
<thead>
<tr>
<th>Gender</th>
<th>Number</th>
<th>Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male</td>
<td>60</td>
<td>73.2%</td>
</tr>
<tr>
<td>Female</td>
<td>22</td>
<td>26.8%</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>Race and Ethnicity</th>
<th>Number</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>White</td>
<td>71</td>
<td>86.6%</td>
</tr>
<tr>
<td>Black or African American</td>
<td>3</td>
<td>3.7%</td>
</tr>
<tr>
<td>Asian American</td>
<td>2</td>
<td>2.4%</td>
</tr>
<tr>
<td>Native Hawaiian or Pacific Islander</td>
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<td>1.2%</td>
</tr>
<tr>
<td>Other</td>
<td>5</td>
<td>6.1%</td>
</tr>
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</table>

<table>
<thead>
<tr>
<th>Age</th>
<th>Number</th>
<th>Sample</th>
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</thead>
<tbody>
<tr>
<td>20-30</td>
<td>32</td>
<td>39.0%</td>
</tr>
<tr>
<td>31-40</td>
<td>18</td>
<td>30.5%</td>
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<tr>
<td>41-50</td>
<td>18</td>
<td>30.5%</td>
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<tr>
<td>51+</td>
<td>14</td>
<td>17.1%</td>
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<tr>
<th>Experience</th>
<th>Mean</th>
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<tr>
<td>Years in Sales at Company</td>
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<td>6.9</td>
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<td>Total Years in Tech Sales</td>
<td>15.3</td>
<td>9.7</td>
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</table>

<table>
<thead>
<tr>
<th>Additional measures</th>
<th>Number (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Role/Title Account Manager</td>
<td>82 (100%)</td>
</tr>
<tr>
<td>Ingroup treatment</td>
<td>48 (58.5%)</td>
</tr>
</tbody>
</table>

**Descriptive Statistics – Trust Measures with Outliers Removed**

Removing the outliers shows significant improvement in both skewness and kurtosis for the new sample n = 82. We found the affective trust to be left-skewed. See Table 4.4 for full details. This can be explained by the expected strong affective trust of the seller and their expert. The means and standard deviations of cognitive and affective trust are very similar, but the skewness of affective trust is high. We can see how these two mathematical findings coexist through the histograms in Figures 4.1 and 4.2. The removal of the outliers causes both skewness and kurtosis for cognitive trust to fall within
± 1, indicating a normal distribution. Measures of Normative Trust and Propensity to Trust have skewness and kurtosis that are well within ± 1, indicating a normal distribution.

Table 4.4

Descriptive Statistics – Trust Measures of Final Sample

<table>
<thead>
<tr>
<th></th>
<th>n=82</th>
<th>Min</th>
<th>Max</th>
<th>Mean</th>
<th>Std Dev</th>
<th>Var.</th>
<th>Skew</th>
<th>Kurtosis</th>
</tr>
</thead>
<tbody>
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<td></td>
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<tr>
<td>Affective__Mean</td>
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<td></td>
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<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>4.00</td>
<td>7.00</td>
<td>6.45</td>
<td>.66</td>
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<td></td>
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<td></td>
<td>.43</td>
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<td></td>
<td></td>
<td></td>
<td>2.74 .526</td>
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<td>Cognitive__Mean</td>
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<td>4.33</td>
<td>7.00</td>
<td>6.46</td>
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<td></td>
<td></td>
<td></td>
<td>.018 .526</td>
</tr>
<tr>
<td>Normative__Mean</td>
<td></td>
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<td></td>
<td>1.17</td>
<td>4.83</td>
<td>3.02</td>
<td>.77</td>
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<td></td>
<td></td>
<td></td>
<td>-.361 .526</td>
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<tr>
<td>Propensity__Mean</td>
<td></td>
<td></td>
<td></td>
<td>2.00</td>
<td>5.00</td>
<td>4.03</td>
<td>.74</td>
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<td>.55</td>
</tr>
</tbody>
</table>

Figure 4.1

Histogram of Affective Trust Responses
Vignette Trust Validity

Our assessment of trust within each vignette was a series of three questions, the third being reverse coded. After adjusting the coding for the third question, we assessed Cronbach’s Alpha for our two control variables. The first control is a vignette conducted assessing the trust of the chosen expert where the seller’s go-to-expert is the most qualified. For the three-item scale, Cronbach’s Alpha (n=82) is .778 indicating an acceptable level of reliability (Carmines & Zeller, 1979). For the second control, the vignette contains no additional information but changes the technology to the one the go-to-expert is least experienced with. The Cronbach’s Alpha for the second control is .708. We consider this scale acceptable for the research.
Assessing Potential Control Variables and Additional Measures

Next, we assess variables for which we may need to control in our model. To do so, we averaged trust and choice across the N vignettes and computed correlations between the potential control variables and those scores. Large correlations would indicate that the control variables accounted for a substantial portion of the variance in the outcomes and may need to be controlled. We determined that we may want to control for normative commitment with trust and propensity to trust with choice. Respectively, normative commitment and propensity to trust both have a significant impact on trust and choice. We have chosen to control for each in the final models — a summary of the potential control variables in Table 4.5.

Table 4.5

<table>
<thead>
<tr>
<th>Potential Control Variables - Pearson Correlations</th>
<th>Trust</th>
<th>Choice</th>
</tr>
</thead>
<tbody>
<tr>
<td>n=82</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gender</td>
<td>-.052</td>
<td>.196</td>
</tr>
<tr>
<td>Ethnicity</td>
<td>.092</td>
<td>.054</td>
</tr>
<tr>
<td>Age</td>
<td>.002</td>
<td>.085</td>
</tr>
<tr>
<td>Years at Cisco</td>
<td>.079</td>
<td>-.024</td>
</tr>
<tr>
<td>Years in Sales</td>
<td>-.035</td>
<td>-.035</td>
</tr>
<tr>
<td>Customer Sector</td>
<td>-.110</td>
<td>.143</td>
</tr>
<tr>
<td>Customer Size</td>
<td>.013</td>
<td>.042</td>
</tr>
<tr>
<td>Propensity to Trust</td>
<td>-.045</td>
<td>.317*</td>
</tr>
<tr>
<td>Normative Commitment</td>
<td>.356*</td>
<td>-.194</td>
</tr>
<tr>
<td>Risk Tolerance</td>
<td>-.053</td>
<td>-.039</td>
</tr>
</tbody>
</table>

*p<.001

We also included supplemental measures of risk-taking and stereotyping. Risk-taking is measured on a scale of 1-4, and participants used the full range of the scale. We found that the Skewness and Kurtosis are very close to 0, indicating a relatively normal distribution. Stereotypes are measured on a scale of 1-7, and participants used most of the
scale, with responses ranging from 1 to 6.67. Both skewness and kurtosis are within ± 1.

A summary of the additional measures is in Table 4.6.

Table 4.6

<table>
<thead>
<tr>
<th>Additional Measures</th>
<th>n=82</th>
<th>Min</th>
<th>Max</th>
<th>Mean</th>
<th>Std Dev</th>
<th>Var</th>
<th>Skew Std Err</th>
<th>Kurtosis Std Err</th>
</tr>
</thead>
<tbody>
<tr>
<td>Risk_taking</td>
<td>1</td>
<td>4</td>
<td>2.20</td>
<td>.656</td>
<td>.431</td>
<td>.044</td>
<td>.266</td>
<td>-.163</td>
</tr>
<tr>
<td>Stereotype_Mean</td>
<td>1</td>
<td>6.67</td>
<td>3.776</td>
<td>1.262</td>
<td>1.591</td>
<td>-247</td>
<td>.266</td>
<td>-.607</td>
</tr>
</tbody>
</table>

Hypotheses

Assessing for Multi-Level Analysis

As stated in Chapter 3, before conducting hypothesis tests, we computed the null (intercepts-only) models for each outcome variable. These models allow the average level of the dependent variable to differ across participants but include no predictors, producing an intraclass correlation coefficient (ICC) to gauge the dependent variable variance at the within-person and between-person levels. An ICC of approximately .05 or higher supports the need for hierarchical linear modeling (LeBreton & Senter, 2008). Data assessed in the model requires centering around a meaningful zero. We chose uncentered for the ingroup and individuating information variables because they are both dichotomous variables. We chose uncentered for the recommendation because we have a meaningful zero (i.e., no recommendation). Using the lme4 package in R, we calculated the null intercepts-only model for the impact of cognitive and affective trust on choice (Bates et al., 2015). The ICC for the model is .78, which is significantly greater than .05, the recommended minimum ICC for multi-level modeling. This model supports multi-level modeling.
Assessing the model for trust as a dependent variable, we tested the intercepts-only equation where our outcome variable is trust. Using the LME package in R, we found that the ICC = .64, which is greater than our rule of thumb of .05. This model supports multi-level modeling. Using an ANOVA test, we compared the random intercepts model with a model including random slopes. We found that there was a significant improvement in the model (p < .001). Therefore, we tested the hypotheses using the random intercepts and random slopes model.

Assessing the model for choice as a dependent variable, we tested the intercepts-only equation where our outcome variable is choice, a dichotomous variable. Testing the null intercepts model for the viability of multi-level modeling, the ICC generated was .78, which is greater than our .05 rule of thumb.

**Hypotheses 1a, 1b**

Hypothesis 1a and 1b suggest that individuals with higher levels of affective and cognitive trust in their go-to expert will be less likely to choose the unknown expert with better technical expertise regardless of our interventions. We also controlled for normative commitment, which was significantly correlated with trust (as reported in Table 4.5). We used grand-mean centering for affective trust, cognitive trust, and normative commitment, creating a meaningful zero. The equation for each model is displayed in Equation 4.1. Neither hypothesis was supported with 1a) affective trust (β_{01}=-1.19, p=.19) 1b) cognitive trust (β_{02}=0.72, p=.40). We cannot reject the null hypothesis in either scenario.

**Equation 4.1**

\[ \text{Choice}_{ij} = \gamma_{00} + \beta_{01} \times (\text{CognitiveTrust}_i) + \beta_{02} \times (\text{AffectiveTrust}_j) + \mu_i + \epsilon_i \]
Hypotheses 2a, 3a, 4a

We tested hypotheses 2a, 3a, and 4a using hierarchical linear modeling with random intercepts and slopes. To test these hypotheses, we leveraged the lme4 package in R.

Hypothesis 2a stated that trust in the chosen expert would be higher when a common ingroup identity is present. The results are not significant for ingroup identity ($\gamma_{01} = -0.12, p = 0.24$), indicating the null hypothesis could not be rejected. Controlling for normative commitment and using a grand-mean-centered result for normative commitment, the null hypothesis could not be rejected ($\gamma_{01} = -0.10, p = 0.29$).

Hypothesis 3a stated that the presence of individuating information would increase the trust in the chosen expert (Equation 4.2). The results were not significant when using the random-intercepts and random-slopes model ($\beta_1 = 0.04, p = 0.28$). Similarly, when controlling for normative commitment, we could not reject the null hypothesis ($\beta_1 = 0.04, p = 0.28$).

Hypothesis 4a stated that trust in the chosen expert would be stronger in the presence of a recommendation of a known and trusted seller. We used a random-intercepts and random-slopes model to test the hypotheses. The results were significant ($\beta_2 = 0.20, p < .001$). Controlling for normative commitment, we found similar results ($\beta_2 = 0.20, p < .001$). The $R^2$ for the model is .04. While the model shows that the presence of a recommendation from a known and trusted seller is positive, it suggests that it accounts for only 4% of the fixed variance in trust of the chosen expert.
Looking at the entire model, we found the $R^2$ for fixed effects is .11, and the total $R^2$ of the model represented in Equation 4.2, including random intercepts and slopes is .80. This model has high explanatory power.

**Equation 4.2**

$$\text{Trust}_\text{Chosen_Expert}_{ij} = Y_{00} + \beta_{1j} \ast (\text{IndividInfo}_{ij}) + \beta_{2j} \ast (\text{Recommend\_Respected}_{ij}) + \gamma_{01} \ast (\text{InGroup}_j) + \mu_j + e_{ij}$$

**Hypotheses 2b, 3b, 4b,**

Hypotheses 2b, 3b, and 4b are all measures of choice, a dichotomous variable. To test these hypotheses, we leveraged a generalized linear model with a binomial link, which is appropriate for dichotomous outcomes. We proceeded using Equation 4.3 below.

Hypothesis 2b stated that the presence of a common ingroup manipulation would increase the likelihood of choosing the unknown expert. Using a random-intercepts model, we found that we cannot reject the null hypothesis as $\gamma_{01}$ is positive but non-significant ($\gamma_{01} = 1.40, p = .20$). Controlling for propensity to trust, we found $\gamma_{01}$ is still positive and insignificant ($\gamma_{01} = 1.08, p = .31$).

Hypothesis 3b stated that the presence of individuation information, or win rate in this case, would increase the likelihood of choosing the unknown expert. We found that hypothesis 3b is positive and significant ($\beta_1 = 1.89, p < .001$), and thus supported. Controlling for propensity to trust, we found the same results. The odds ratio for this variable is 6.6, indicating that in the presence of individuating information, it is 6.6 times more likely that an individual will choose the unknown expert.

Hypothesis 4b stated that a recommendation by a known and trusted seller would increase the likelihood of choosing an unknown expert over either of the other two
conditions (either no recommendation or a recommendation from an unfamiliar peer). We found that the hypothesis is supported ($\beta_2 = 1.09, p < .001$). Again, controlling for propensity to trust, we found the hypothesis is supported ($\beta_2 = 1.10, p < .001$).

For hypotheses 2b, 3b, and 4b, we also controlled for propensity to trust as indicated by our Pearson Correlation. The model including hypotheses 2b, 3b, and 4b and propensity to trust has a pseudo-$R^2$ of 0.17, indicating that the fixed-effects of our variables account for 17% of the variation in choosing the unknown expert. The $R^2$ for the entire model, controlling for propensity to trust, is $R^2 = .86$, demonstrating high explanatory power. A summary of detailed findings for hypotheses 2b, 3b, and 4b are found in Table 4.7.

**Equation 4.3**

$$ \text{Choice}_{ij} = \gamma_{00} + \beta_{1j} \cdot (\text{IndividInfo}_{ij}) + \beta_{2j} \cdot (\text{Recommend\_Respected}_{ij}) + \gamma_{01} \cdot (\text{Ingroup}_{ij}) + \mu_j + \epsilon_{ij} $$
Table 4.7

Summary of Results for Hypotheses 2, 3, and 4

<table>
<thead>
<tr>
<th>Predictors</th>
<th>Estimates</th>
<th>CI</th>
<th>p</th>
<th>Odds Ratios</th>
<th>CI</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>( Intercept )</td>
<td>4.47</td>
<td>4.30 – 4.63</td>
<td>&lt;0.001</td>
<td>0.31</td>
<td>0.05 – 1.40</td>
<td>0.115</td>
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<tr>
<td>Individuating Info</td>
<td>0.04</td>
<td>-0.03 – 0.10</td>
<td>0.274</td>
<td>6.60</td>
<td>3.23 – 13.19</td>
<td>&lt;0.001</td>
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<tr>
<td>Recommend. (1= Respected Peer)</td>
<td>0.20</td>
<td>0.11 – 0.29</td>
<td>&lt;0.001</td>
<td>3.00</td>
<td>1.51 – 5.89</td>
<td>0.002</td>
</tr>
<tr>
<td>Common Ingroup Identity</td>
<td>-0.10</td>
<td>-0.29 – 0.09</td>
<td>0.285</td>
<td>2.94</td>
<td>0.47 – 35.30</td>
<td>0.204</td>
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<td>Normative Commitment</td>
<td>0.21</td>
<td>0.09 – 0.33</td>
<td>0.001</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Propensity to Trust</td>
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<td></td>
<td></td>
<td>7.17</td>
<td>1.66-30.89</td>
<td>0.008</td>
</tr>
</tbody>
</table>

Random Effects

<p>| | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>σ²</td>
<td>0.07</td>
<td></td>
<td>3.29</td>
</tr>
<tr>
<td>τ00</td>
<td>0.30</td>
<td>Number</td>
<td>15.67</td>
</tr>
<tr>
<td>ICC</td>
<td>0.77</td>
<td></td>
<td>0.83</td>
</tr>
<tr>
<td>N</td>
<td>82</td>
<td>Number</td>
<td>82</td>
</tr>
<tr>
<td>Observations</td>
<td>492</td>
<td></td>
<td>492</td>
</tr>
<tr>
<td>Marginal R² / Conditional R²</td>
<td>0.112 / 0.796</td>
<td>0.167 / 0.855</td>
<td></td>
</tr>
</tbody>
</table>

Supplemental Analyses

Financial Risk Tolerance and Normative Commitment

In the study, we collected information on participants’ financial risk tolerance as well as their normative commitment to their organization. Leveraging the Survey of Consumer Finances (SCF), we coded the answers to the four questions from zero to
three; zero being the least financial risk tolerance and three being the greatest. Using linear regression with risk tolerance being the independent variable and normative commitment the dependent variable, we found that financial risk tolerance is negatively correlated with normative commitment ($\beta = -0.14$, $p = 0.01$, $R^2 = 0.01$). However, financial risk tolerance was not found to be correlated with either trust or choice in the vignettes.

**Propensity to Trust, Affective Trust, and Cognitive Trust**

Having collected information on the participant’s propensity to trust as well as their affective trust in their go-to expert, we used linear regression with propensity to trust as the independent variable and affective trust as the dependent variable. Propensity to trust is positively correlated with affective trust in the go-to expert ($\beta = 0.10$, $p = 0.01$, $R^2 = 0.07$). Assessing propensity to trust with cognitive trust in the go-to expert, we found that there is no significant correlation ($p = 0.664$).

**Stereotypes**

We found no significant relationships between stereotyping of engineers and any other variable collected in our study.

**Open Response Question**

Participants were asked a single open-ended question at the end of the survey: “What are your main points of consideration when selecting an expert to attend a customer meeting?” The question required a response, but a single word would suffice.

To analyze these data, we calculated the frequency with which participants wrote about technical competence and social skills. Words grouped into technical expertise were: knowledge, knowledgeable, experience, expertise, technical aptitude, technical
skill(set), and technical acumen. Words grouped for social adaptability were: flex
approach, personable, listening, professional, empathy, humility, customer fit, social
grace, social skills, customer presence, ability to communicate, ability to read social cues,
social awareness, and personal skills.

Of the 88 respondents in our final analysis, 61 used words to describe technical
expertise. Of those 61, 44 used words describing both technical expertise and social
adaptability (see below for a list of words associated with each of these). Thirteen of
those respondents listed words describing social adaptability before expertise in their
free-form response, suggesting that social adaptability was most salient for almost 1/3 of
those sellers. Additionally, 13 individuals specifically mention the word “trust” either
between the customer and the expert or between the seller and the expert. Finally, five
individuals mentioned seeking a recommendation for the expert.

**Trust and Choice**

The measure of trust within each vignette is the trust in the chosen expert for that
scenario. We found that trust is negatively correlated with choice. Those who choose an
unknown expert have less trust in them for that scenario than when they choose their go-
to expert ($\beta = -0.15$, $p = 0.004$, $R^2 = 0.017$). Because the unknown expert is represented
as “1” and the go-to expert is represented as “0”, we found that after choosing the
unknown expert for the scenario, trust in that individual is less than it would be for their
go-to-expert. The key is that we were able to influence the participant to choose the
unknown expert and, with a recommendation, trust them more than they would have
without that treatment.
We found that cognitive trust in the go-to expert positively correlates to trust in the chosen expert ($\beta = 0.183$, $p < 0.001$, $R^2 = 0.017$). Selecting only cases where the unknown expert is chosen, we found that the relationship between cognitive trust in the known expert is positively correlated with trust in the chosen unknown expert ($\beta = 0.149$, $p = 0.007$, $R^2 = 0.027$). Selecting only cases where the known expert is chosen, the relationship between cognitive trust in the known expert is positively correlated with trust in that same expert in the vignette utilizing the expertise in which they are least capable ($\beta = 0.15$, $p = 0.011$, $R^2 = 0.029$), but with decreasing significance.

We found no significant relationship between affective trust in the go-to expert and trust in the chosen expert until we exclude cases where the known expert was chosen. There is significance in the model for a quadratic relationship between affective trust and trust in the chosen unknown expert ($\beta_1 = -0.123$, $\beta_2 = -0.214$, $p = 0.004$, $R^2 = 0.041$) when removing scenarios where the known expert was chosen. This means that as affective trust in the known expert increases, so does trust in the unknown expert until you get to approximately the mean for affective trust. At that point, the trust in the unknown expert is negatively related. Mathematically, this outcome may also be influenced by the number of responses along the curve. There are 23 responses between -2 and <0 for centered affective trust. There are 22 responses between 0 and 1 for centered affective trust. The distribution of the responses may weigh in on this result. With that, it is possible that when seller has more than average affective trust for their go-to expert, they may have less trust in an unknown expert when they choose that expert for a scenario.
Figure 4.3

Affective Trust in Go-to-Expert vs Trust in Unknown Expert - Quadratic

Summary

We found mixed outcomes in the hypotheses. Hypotheses 1 and 2 were not supported in the research. Hypothesis 3 was partially supported, and hypothesis 4 was fully supported. See Table 4.8 for additional information.

Table 4.8

Hypotheses Summary

<table>
<thead>
<tr>
<th>Hypotheses</th>
<th>Trust</th>
<th>Choice</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Affective and Cognitive</td>
<td>Not Supported</td>
<td>Not Supported</td>
</tr>
<tr>
<td>2. Ingroup</td>
<td>Not Supported</td>
<td>Not Supported</td>
</tr>
<tr>
<td>3. Individuating Information</td>
<td>Not Supported</td>
<td>Supported</td>
</tr>
<tr>
<td>4. Respected eRecommendation</td>
<td>Supported</td>
<td>Supported</td>
</tr>
</tbody>
</table>
Chapter 5 – Discussion

In business-to-business sales (B2B) environments, a salesperson’s (seller) ability to match the customer’s business needs to their firm’s products is key to their firm’s success (Shi et al., 2017). In highly technical B2B sales environments, the seller may engage technical experts to help them establish the ability of the firm’s product(s) to address the customer’s business challenge (Goodwin-Sak, 2019). There are several factors that introduce risk to the seller in the scenario, including risk to their reputation with the customer and their compensation structure. Social network theory suggests that sellers will choose to engage a technical expert with whom they have built a relationship, or strong ties, over others (Granovetter, 1973; McPherson et al., 1992), even if that expert’s skills are not a strong match for the customer’s situation. Additionally, technical experts are often stereotyped as having low interpersonal skills (Akbulut-Bailey, 2013; Enns et al., 2006; Galetta, 2007), meaning that it may be difficult for the seller to know if the expert can adapt to social cues in a customer meeting.

The underpinnings of the study rely on the ability to establish initial or swift trust in an unknown expert to encourage the seller to choose and work with that expert in the scenario, overcoming their established trust connection with their go-to expert. The study focused on the question: can an intervention of data, trust transference, ingroup identity, or a combination, influence the choice of expert a salesperson engages for a customer meeting? It is in this context that we discuss the key findings.

Key Findings

From this study, there are several key findings that are applicable to both academic and practitioner research.
Finding 1 – Common Group Identity Model – Recategorization

Past research suggested that superordinate identifiers can create an ingroup identity that will increase trust. This is grounded in the concept of initial trust or swift trust that may be influenced by “institutional cues” to indicate that a person may be trustworthy (McKnight et al., 1998). The objective of these interventions is to overcome any outgroup perceptions developed through the social network (Abrams and Hogg, 2006) and from negative stereotypes (Akbulut-Bailey, 2013; Enns et al., 2006; Galetta, 2007). We used multiple treatments to generate the superordinate identifier of belonging to the corporation (Cisco). However, this manipulation produced no significant effects on trust, stereotyping, or choice. While several studies indicate we should find a significant positive correlation between ingroup and trust and/or choice, we find that with trust, there is potentially a negative relationship, but the findings are not significant. Additionally, we found no statistically significant relationship between stereotypes and the ingroup treatment.

Klar (2018) performed an experiment on partisan women to understand the implication of applying the superordinate identifier of gender. When gender was applied, the women showed greater bias toward each other. Research from Dach-Gruchow and Hong (2006) studied the superordinate identifier of “American” following Hurricane Katrina, finding it did not unify Black and White Americans. Rutchick and Eccleston (2010) found the same when studying partisan groups within the US. They found that when a speaker of a different party utilized the term “American,” it increased rather than decreased bias. Brewer (1996) determined that for the superordinate identifier to work, there must be a common perception of its definition and common goals. Related to our
study, we see three possible explanations for the non-significant findings: a) participants already saw themselves as part of a common ingroup, or b) the theory might be disconfirmed in this context. We believe there is more to be explored in this area. To find more, see Future Discussions.

**Finding 2 – Transfer of Trust**

Theory suggests that we can leverage the transfer of trust from a respected seller to increase the trust in the chosen expert as well as the likelihood of choosing the unknown expert. Supporting the transfer of trust theory, the recommendation from a known seller is associated with an increase in trust by approximately 20%. The full model, including random effects and other fixed effects, explains 80% of the variation in trust. Additionally, the odds ratio for choosing an unknown expert when a respected seller recommendation is present is 3.00, *p < .001*, indicating it is *three times* more likely that the seller will choose the unknown expert in the presence of a respected seller’s recommendation. Both Stewart and McKnight find evidence that it is possible to transfer trust from a known party to unknown parties (2003, 1998). We find a unique application in that the transfer of trust was done through a tool and not through live conversation. The simple indication of trust in the unknown expert from a respected seller increased both the likelihood of choosing the unknown expert and the trust in that expert. While we did not explore the strength of the relationship between the trusted seller and their respected peer who recommended the expert, the recommendation from a respected peer emphasizes the results from Stewart (2006) and extends the context of application into sales and accelerating trust development with experts. This research also indicates the applicability of social network theory to engaging experts. Granovetter’s research (1973)
suggests that the knowledge engaged through these weaker social ties will be of higher quality. This expands Grannovetter’s body of research into both the realm of sales and engaging experts.

While the recommendation is the most impactful manipulation in the study, it is mentioned relatively infrequently in the open text responses. In the open text analysis, only five respondents indicated that they look for a recommendation in choosing an expert. One possibility is that the participants were thinking specifically of qualities in the expert, rather than how they identified the expert for assessment. However, another possibility seems to be that participants may not be consciously aware of which factors are most influential in their decisions.

In a study of how patients choose a physician, participants were asked to rank a list of attributes or information that were most important to them in selecting a physician. Board certification of the physician and professional appearance of the physician and office were at the top of the list, followed by recommendations from friends/family. Specialization in a particular illness was rated lower than recommendations from friends/family (Bornstein et al., 2000). In two separate studies on physician selection, patients had the opportunity to obtain information on a physician’s practice (the most important factors to the patient) prior to engaging that physician, but did not do so (Bornstein et al., 2000; Salisbury, 1998). In Salisbury’s study (1998), most respondents indicated they initially found out about a physician’s practice by asking friends or neighbors. One conclusion we may draw from these similar studies is that individuals may place importance on specific factors for experts when they pause to consider their priorities but could be unaware of them otherwise. Another possibility is that they are
simply not compelled to spend the effort in gathering the information, instead relying on recommendations from friends and family.

The conclusion of this finding is that sharing expert recommendations from respected peers will significantly increase both choice to work with that expert as well as initial trust in that expert.

**Finding 3 - Individuating Information**

Hypothesis three suggests that the presence of individuating information will impact both trust and choice. This hypothesis was developed on the foundation of the work from Krueger and Rothbart (1988), suggesting that behaviorally relevant information may help disregard stereotypes as well as the previous research from Goodwin-Sak (2019), that knowledge of technical expertise and interpersonal skills would facilitate the selection of an expert. We leveraged the concept of a win-rate to give the participants a quantifiable understanding of the individual’s combined technical and interpersonal skills. It was interesting to note that this manipulation was not significantly related to trust, but it was significantly related to choice, with participants being *more than six times as likely* to choose the recommended expert when this win rate was present than when it was absent (note that in this study, the win rate was always favorable).

The open text question provided some insights from the participants as well. We believe the concept of a win-rate resonated with sellers, giving them confidence to choose an expert. While win-rate cannot be specifically correlated to technical expertise or social adaptability, we believe the concept that the expert “won” opportunities triggered the main concepts that the sellers associate with a choice of an expert. With 75% of respondents mentioning technical expertise as a point of consideration and 54% of the
respondents using words that express both technical expertise and social skills or adaptability as key considerations, we believe that these concepts were highly correlated with the concept of win-rate, which was the original intention when choosing this phrase. From this we conclude that presenting individuating information on outcomes related to engaging the expert will significantly increase the likelihood of choosing to work with that expert.

**Finding 4 – Cognitive and Affective Trust**

The study’s foundation relies upon the expectation that sellers develop both cognitive and affective trust in their go-to experts. The results clearly show that the participants have high affective trust in their go-to experts beyond a normal distribution. In the final sample of n = 82, skewness for affective trust was -2.66 and kurtosis was 2.74, while cognitive trust follows a normal distribution. The mean of cognitive trust was 6.46 (on a scale of 1 to 7) and the mean of affective trust was 6.45. Both cognitive and affective trust have similar standard deviations, .65 and .66 respectively. Figures 4.1 and 4.2 demonstrate how the means and standard deviations can be so similar, while affective trust is skewed. It appears that sellers in this sample have very high affective trust with their experts. While the mean of cognitive trust is high, there is no indication that sellers have disproportionately high cognitive trust in their experts.

We expected that sellers with higher levels of affective and cognitive trust in their go-to experts would be less likely to choose an unknown expert. While the results show that positive affective trust in a go-to expert are negatively related to choosing an unknown expert, the results are insignificant, contradicting our expectation. Similarly, we cannot validate that cognitive trust in an expert influences choice in the expert.
potential reason is that the seller may use a preparation meeting to “buffer” any negative effects of their choice, so initial trust is inconsequential in choosing an expert. In interviews with sellers, they speak of including their go-to experts in preparation meetings where they must engage unknown experts (Goodwin-Sak, 2019). If the seller anticipates inviting their go-to expert to a preparation meeting with the unknown expert, this could create a scenario where there is transparency in the process, reducing any potential negative consequences in the seller and go-to expert relationship. It is also possible that through that preparation meeting, trust is transferred from the go-to expert to the seller. In other words, if the seller trusts their go-to expert, and the expert trusts the unknown expert after the preparation meeting, the seller will have increased trust in the unknown expert.

While we saw no correlation between cognitive and affective trust and choice, we did find interesting relationships between affective trust and cognitive trust in the go-to expert and trust in the chosen expert. Cognitive trust in the go-to expert is positively correlated with vignette-level trust in the chosen expert. Looking at all cases together, cognitive trust in the go-to expert explains 1.7% of the trust in the chosen expert. Isolating only the cases where the unknown expert is chosen, the strength of the relationship between cognitive trust in the known expert is stronger, explaining 2.7% of the trust in the unknown expert. Isolating the cases where the known expert is chosen, the results are slightly less significant $p = 0.011$, but still explaining 2.9% of trust. This suggests that sellers with strong cognitive trust in their experts may have increased trust in other experts in a similar field.
When only looking at cases where the unknown expert was chosen, we found a quadratic relationship between affective trust in the known expert and the trust in the unknown expert. When affective trust in the go-to-expert is lower, trust in the unknown expert chosen is also lower. As affective trust increases, so does the trust in the unknown expert until just before the mean of affective trust. After that point, trust in the unknown expert decreases as affective trust in the go-to expert increases. A potential explanation is that increasing affective trust can be transferred to an unknown expert. But very high affective trust causes the seller to have increasing concern about negatively impacting their relationship with their go-to expert if they choose another expert to work with.

**Implications for Research**

A key finding of this study is that common ingroup identity was not effective in affecting choice of or trust in an unknown expert. Two potential implications for research are a) testing for a common definition of an ingroup identifier before application and the resulting outcomes, and b) the lack of significant findings may have implications for de-confirming the original research.

Another key implication is that individuals can articulate the key factors in choosing experts, but they may not leverage the same factors in making the choice. That requires additional academic research to identify both the perceived requirements and the applied requirements of individuals in expert selection.

Additionally, we found a correlation between affective trust in co-workers and normative commitment to the go-to expert. Meyer and Allen (1991) indicate a potential correlation between affective commitment to an individual and normative commitment to an organization, but co-worker affective trust is not clearly articulated in the model.
Normative commitment is a measure of the sense of obligation of an individual to continue working with their peers. There have been studies on the role affective trust between employees and leaders plays in normative commitment (Chiang & Wang, 2012; Miao et al., 2014), but nothing on affective trust and normative commitment with peers. Simply put, it is difficult to overcome the sense of obligation and academia is relatively silent on the issue.

We found a significant negative relationship between financial risk tolerance and normative commitment to the go-to-expert. Meyer and Allen’s (1991) three-component model of commitment suggests that individuals who are financially risk averse would have high continuance commitment, but not necessarily high normative organizational commitment. The questions regarding normative commitment are focused on the morality of leaving coworkers. Further studies could be conducted to determine if there is a relationship between low financial risk tolerance and the sense of moral obligation to coworkers.

**Implications for Practice**

To build loyalty within organizations, firms often encourage their employees to identify with the firm’s brand. We found no change in the perception of stereotypes from the in-group manipulation including the firm’s brand in this case. In fact, there is some suggestion that the manipulation causes a negative impact on trust. This study suggests the firm should spend more time on defining the brand and ensuring all employees have a similar view of that brand prior to invoking it as a common ingroup. Without doing so, they may be causing greater bias and/or decreased trust within their organizations.
We found that in a sales environment, we increase the probability of selecting an unknown expert when we present individuating information that is prioritized by the seller. As suggested in the introduction, accelerating a connection between a seller and the best expert for a customer sales opportunity could result in a higher win-rate and increased revenue. Understanding the important factors of employees in their decisions to work with an expert can give businesses the information necessary to facilitate connections. Businesses can use this information to foster new connections among individuals, increasing productivity, and increasing business agility.

Extending these results suggests that deliberate networking events, designed to build relationships of sellers and technical experts, could help generate trust. The social networking literature supports this finding. Importantly, our study suggests that positive recommendations from known and respected network connections are key, and that a recommendation from an unfamiliar peer had little effect.

Finally, the supplemental research identified that cognitive trust in an individual from a subgroup increases trust in other unknown individuals from that same subgroup. Creating environments where unique subgroups can develop cognitive trust with individuals in another subgroup, along with reiterating the connection between cognitive trust in the individual and their subgroup identification, may increase trust between groups within an organization. Again, this could increase productivity and agility in an organization.

Limitations

As with any other research method, the vignette has the potential to have challenges with both internal and external validity. The vignette may be prone to
challenges with internal validity if multiple scenarios are presented, which may inadvertently affect the respondent’s subsequent choices or where the respondent may guess the underlying question and modify their response to accommodate external expectations or social norms (Atzmüller & Steiner, 2010; Steiner et al., 2016). We took significant steps to mitigate this as a concern. The vignette experiment can also suffer from low external validity because the setting may be over-simplified.

The concept of trust requires risk in most definitions (see Table 2.1 for a list of reviewed definitions), including the definition we use for this study, Whitener et al. (1998). This required our study to introduce perceived risk into our vignettes. However, we may have introduced too much risk, which may have had a negative impact on the validity of the findings. The study presented participants with four technology categories in which they were to force-rank their go-to expert. The subsequent vignettes presented scenarios in the context of the go-to expert’s least-ranked technical competency. When presented with the scenario of the go-to expert’s highest-ranked technology area, only six of the 89 respondents chose the unknown expert. When switching to the go-to expert’s least-ranked technology competency, 44 of the 89 chose the unknown expert in the control vignette. We believe this immediately introduced too much risk to the seller and they were pre-dispositioned to find another expert to engage in the opportunity. See the section titled Future Directions for additional information.

The research was conducted during the COVID-19 pandemic. This may have had a negative effect on ingroup identity. Additionally, the study may have shown significantly greater risk than necessary to provide additional insights on the interventions.
**Future Directions**

The present study presented a uniformly high level of risk across scenarios. Future studies could simulate varied risk to better understand which interventions work best for a given risk environment. This could provide greater insights into the interventions that did not show statistical significance.

We found it interesting that the common in-group manipulation (while not reaching significance), was negatively correlated to trust in the study. This, combined with some negative results from past studies, suggests that there could be situations in which reminding individuals of a shared identity could conceivably produce counterintuitive effects. Additional research on the potentially harmful impacts of superordinate identifiers in organizations as well as correlation to organizational sentiment would offer new insights to both practitioners and academics alike.

While many of our interventions were not statistically significant, the overall effects for some individual sellers was very large as is seen in the conditional $R^2$ for both choice and trust. Future research could identify moderators that exist to influence seller choice and trust in experts.

This study used vignettes to minimize any impact on sellers and their go-to experts. These vignettes were designed to mimic a database that could potentially match experts to specific sales jobs. If such interventions are applied in practice, research should be done on techniques to mitigate any potential negative impacts to the go-to expert, the relationship between the seller and their go-to-expert, as well as any impacts on overall organizational commitment.

Finally, as we identify manipulations for trust and biases, we must explore
the ethical considerations in a corporate environment. Much research has been done on ethical considerations when using artificial intelligence and machine learning. A single search on Google Scholar finds more than one million articles on “ethics artificial intelligence.” We could find no research on the ethical considerations of manipulating trust, nor when doing so in a corporate environment. While this could positively impact organizational efficiency, concerns over privacy or intentionally leveraging human heuristics to create an advantage in an organization may put the organization at odds with the perceived autonomy of its individuals. Additionally, the most effective manipulations may never be recognized by employees, introducing the complexities of ethics. This requires both academic and practitioner research as technology is increasingly integrated into daily life and decision making.

**General Conclusions**

This study demonstrates that it is possible to use manipulations such as presenting individuating information and peer recommendation to increase the likelihood of a seller choosing an unknown expert and having increased initial trust of that expert. This research expands upon existing academic knowledge and gives practitioners new tools to improve productivity, agility, and to foster greater inclusion in their organizations.
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Appendix A

Recruiting Email – Full Study

Greetings! I am conducting a study to complete the dissertation requirements for the Doctor of Business Administration to answer an important research question. If you’re a seller in the United States who has been at Cisco for at least one year, your response is requested.

This link will take you to an experiment that takes approximately 20 minutes to complete. After answering some basic demographic information, you will be presented with a few sales scenarios, finishing with a few additional questions. I know your time is incredibly valuable. In gratitude for your help, upon completion of the experiment, you’ll be redirected to a form to submit your email address for entry into a raffle to win one of eight prizes valued at approximately $300.

The prized from which you can choose are:
1) Bose Home Speaker 500 - $299
2) Yeti Soft Cooler Flip Top 18 - $299
3) Yeti Soft Cooler Backpack - $299
4) Tiffany Paloma Picasso Olive Leaf Heart Pendant $300
5) A $300 Donation to the charity of your choosing through Bright Funds.

Your identity will not be linked to your study responses, and any information provided will be kept private and protected. Click here to join the study!

Cisco Systems does not sponsor this research; however, some of the learnings from this research may be used to enhance future applications and sales tools.

Thank you,

Cindy Goodwin-Sak

Recruiting Email – Pilot Study

Greetings! I am conducting a study to complete my dissertation for a Doctor of Business Administration. Additionally, we may be able to use the results from this research to make improvements to systems at Cisco. I would greatly appreciate your help in accomplishing this life goal.

The first step in this process is conducting a pilot study to get feedback on the realism, flow, and clarity of the questions asked. The link below will take you to the pilot survey
that will take approximately 15-20 minutes to complete. After answering some basic demographic information, you will be presented with a few scenarios to answer and asking for feedback on the questions.

I know your time is incredibly valuable and I could never repay your kindness in sharing your time with me. However, upon completion, I would like to share a token of appreciation and gratitude for your efforts in helping me complete my research. You will have the opportunity to choose from a wide selection of $10 gift cards specially selected for Australia.

We have constructed the survey so that responses are anonymous, and your identity cannot be recreated. Following the completion of the survey, you will be routed to a separate survey to retrieve your gift card. Your identity will not be linked to your study responses, and any information provided will be kept private and protected.

Cisco Systems does not sponsor this research; however, some of the learnings from this research may be used to enhance future applications and sales tools.

Thank you,

Cindy Goodwin-Sak
Appendix B – Consent Form

College of Business Administration
Informed Consent for Participation in Research Activities
Engaging Experts

HSC Approval Number __287444____

Principal Investigator: Cindy Goodwin-Sak  PI’s Phone Number: (913) 481-9077__

1. You are invited to participate in a research study conducted by Cindy Goodwin-Sak (an individual) and Dr. Stephanie M. Merritt (dissertation advisor).

2. Your participation will involve answering questions related to your demographic information and your current work environment. You will also be presented with several fictitious but realistic scenarios regarding sales. Following the scenarios, you will be asked some additional questions to complete the survey asking you some more questions about yourself and your attitudes. We expect that the study will take most participants approximately 15-25 minutes to complete.

3. The risks or discomforts in this research are intentionally minimized. Any information you share is anonymized to the researcher's best ability; your identity will not be linked with your responses. After completing the study, you’ll be redirected to a separate survey to provide your information for receiving payment. Additionally, the researcher has asked for information to disguise the participants and/or others around the participants to minimize any negative impact on any individuals referenced in the study.

4. There are no direct benefits for you participating in this study.

5. Your participation is voluntary, and you may choose not to participate in this research study or withdraw your consent at any time. You will NOT be penalized in any way should you decide not to participate or withdraw. However, to receive compensation, you must reach the study's end and provide your contact information for compensation.

6. We will do everything we can to protect your privacy. Your identity will not be linked with your responses and will only be collected separately for compensation purposes. Any information you provide to personalize the scenarios will be anonymized after data collection and before use in the study. In rare instances, a researcher's study must undergo an audit or program evaluation by an oversight agency (such as the Office for Human Research Protection) that would lead to the disclosure of any other information collected by the researcher.

7. If you have any questions or concerns regarding this study, or if any problems arise, you may call the principal investigator (phone number above). You may also ask questions or state concerns regarding your rights as a research participant to the Office of Research, at (314) 516-5899.

I have read this consent form and have been given the opportunity to ask questions. I will also be given a copy of this consent form for my records. I hereby consent to my participation in the research described above.

Please download a copy of this consent form for your records.

☐ I consent to participate
☐ I do not consent to participate (exit the study now):