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Could Alexa Increase Your Social Worth?

Peter Tripp

COULD ALEXA INCREASE YOUR SOCIAL WORTH?

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Peter Tripp

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Advisor: Dr. Daniel Baack

Author: Peter Tripp
Title: Could Alexa Increase Your Social Worth?
Advisor: Dr. Daniel Baack
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ABSTRACT

People have historically used personal introductions to build social capital, which is the foundation of career networking and is perhaps the most effective way to advance a career (Lin, 2001). With societal changes, such as the pandemic (Venkatesh & Edirappuli, 2020), and the increasing capabilities of Artificial Intelligence (AI), new approaches may emerge that impact societal relationships. Social capital theory highlights the need for reciprocal agreements to establish the trust between parties (Gouldner, 1960). My theoretical prediction and focus of this research include two principles: The impact of reciprocity in evaluating trust of the source of the introduction and the acceptability of AI in interpersonal relationships. I test this relationship through the creation of plausible vignettes that the participants may have encountered in business. The results show that a higher trust of AI and could replace one side of the relationship, thus reducing the dependency on or eliminating reciprocal behavior.

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In the immortal words of the great Cicero “There is no duty more indispensable than that of returning a kindness. Kindness is produced by kindness.” I can’t thank the people enough that have shown me kindness through their dedication and support on my extended journey through academia.

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CHAPTER I: INTRODUCTION

In each of us, there is another whom we do not know. ~Carl Jung

Since the dawn of history. people have interacted face-to-face and building a community of network connections affords many opportunities and protections. Outside the family, one's personal network is the crucial ecosystem for protecting and advancing these key moments. Intra-connected communities have been essential for people in supporting and surviving wars, protests, stressful moments, and celebration of successes (for instance, Black Lives Matter (BLM) or Captain Sully). The BLM movement galvanized a cross-race group that created strong ties based on a political stance, whereas the crisis of the Miracle on the Hudson (Langewiesche, 2009) built strong ties with the passengers and the hero captain who saved their lives. Building social capital driven networks requires interactions to establish capacity, access channels that have compatibility, and access channels that are willing to provide help. Unsurprisingly, research has shown that building your professional network will enhance employment outcomes (Adler & Kwon, 2002; Batistic & Tymon, 2017; Lin, 1999; Wolff & Moser, 2009).

A professional network that has extensive reach has a mixture of components. It includes several tight connections with those that you interact with and trust on a regular basis as well as weaker connections that you still have mutual. Social capital is "the networks of relationships among people who live and work in a particular society, enabling that society to function effectively" (Onyx & Bullen, 2000, p. 7). Research about how diverse the ties should be has sparked debate between the two views. Pfeffer's (1983) research states the problem is diversity since it introduces potential gaps that deter positive teamwork. Alternatively, Caldwell's (1992) research argues that "members who have enters the organization at different times know a different set of people and often have different technical skills and different perspective that result in higher performance" (p. 15). Caughlin & Sharabi (2013) extended this research to interpersonal networks and determined "higher social capital can be generated through the interactions derived from highly diverse members" (p. 15).

Thus, improving social capital involves access to a continuous flow of social resources as well as access to potential connections outside one's immediate sphere, while still engendering their current community. The process evolves into multiple stages of initial relationship building and then goal orientation, which includes mentoring for career advancement and the organization achieving objectives. Trust is critical for progressing along the relationship continuum from generation to cultivation to utilization, or from stranger to recognized partner. As a result of building these cohesive ties, individuals create a more dynamic community to leverage, tackle, and solve dilemmas; create career opportunities; and face crises. Social networks have rapidly become a mainstay in society and serve as a centralized communication platform for communication, updating or interacting with a group of loosely connected people (Scott, 1988). The characteristics (capabilities, expertise, level of connection) of a social network define the value of the social capital of its individual actors. Crenshaw & Robinson (2006) show how in dissimilarity to financial and human capital, social capital focuses on relations between persons:

> Social capital is basically an individual-level trait, the accumulated trust/good-will/favors/familiarity a person has built up with others. Just as you have financial capital to spend/invest, you also have social capital to spend/invest (or not). Social capital is accrued through social networks, generally - and such networks cannot be reduced to the individual level (they are higher-order phenomena and have true social structure - a person occupies a position in a network). While it's true that people talk about high social capital societies and such, like most social characteristics that's simply the average aggregation of individual-level traits. (p. 204).

A social network is one modality for leveraging social capital through nodes (or members of the network) that are units linked through relations through familiarity or referential positioning such as shared context (Caughlin & Sharabi, 2013). Increasingly, these networks are scaled using technology as the connective pipeline. Facebook and LinkedIn are notable leaders in the social networking space, with the latter being recognized in the business space as the social network of choice for business professionals (Banerji & Reimer, 2019).

The social networking space has given rise to the growth of Artificial Intelligence (AI) due to increased access to data and computing power (Bostrom, 2014). "AI refers to a digital computer's or a computer-controlled robot's, ability to do tasks that are typically associated with intelligent beings "(Clarke, 2019, p. 423). AI is the foundation for many applications, including advanced search engines (e.g., Google), recommendation systems (used by Netflix and Amazon), systems for understanding human speech (e.g., Siri and Alexa), self-driving cars (e.g., Tesla), and for challenging the best players in strategic gaming (such as GO and StarCraft)

(Gibney, 2017). AI is advancing into new frontier spaces that are not typically associated with technical competency, such as art (Liu, 2020) and human emotions (Prentice et al., 2020). Significant research has been done on the relationship between social capital and trust, and there is an evolving field of research on trust with AI, but to date, there is limited research on the relationship between AI and social capital. This research will explore the potential of AI to serve as a social capital conduit in the form of a recommendation engine and to evaluate trust in the source of the recommendation as it relates to reciprocity. A formal research question would be: could AI help promote your social capital?

This dissertation is broken into five chapters. Chapter 2 encompasses a review of social capital literature. I start with an overview of the historical and current definitions. I discuss the three types of reciprocity and provide examples of where it is most used. My intent is to purposefully create a social capital environment using a business scenario and assess the perceptions created by the individual's view of the source of recommendation. Having summarized the social capital literature, I then examine the history of AI and the current literature on AI. I narrowed my scope to human computer interactions (HCI) with AI, given the depth of the field and my focus on this component.

In chapter 3, I introduce the theoretical model for the perception of reciprocity and propose that there is a link between the source of the recommendation and trust level. Additionally, I leverage the Technology Acceptance Model (TAM) for understanding how one may have behavioral attitudes toward technology. First, I hypothesize that participants who are generally favorable toward technology will be more inclined to use AI as a source of information. Second, given that AI has seen accelerated capability through new technology, and it is used widely in newer social media applications (Gursoy et al., 2019), I hypothesize that younger participants will be more amenable to the AI recommendations, whereas an older participant class may have more caution towards the AI recommendation. Third, I manipulate the element of reciprocity in both sources of recommendations, and I hypothesize that reciprocity will have an influence on the trust for a human recommendation.

Chapter 4 contains a summary of the analysis that was conducted. A regression was performed for Hypothesis 1 and 2 showing direct effects and an ANOVA was conducted to test the 3 Hypothesis through the interaction. Participants that were favorable toward technology showed a stronger trust for AI as a source of recommendation. Age showed a negative correlation in trust of AI for older participants. For the last hypothesis results indicated that respondents reacted to the presence of reciprocity when offered a sourced recommendation.

Chapter 5 concludes with a discussion of Chapters 2-4, implications both theoretical and practical, and limitations. The stability of building social capital may be hindered as stronger relationships are built with AI and researchers should explore where expectations in an interpersonal relationship may not carry over to a relationship with a machine. AI platform developers should be cognizant of the lack of expectations that a human-AI relationship may have and what influences it may have on the human agent in the relationship. The findings from this study provide guidance that individuals should be aware of the relationships that are developed with AI-based agents and where this may be helpful and hurtful in their social capital ecosystem.

CHAPTER II: LITERATURE REVIEW

"Fish do not know they are living in water, and members of the middle-income sector are not aware of the social capital that surrounds and sustains them." — Peter Temin

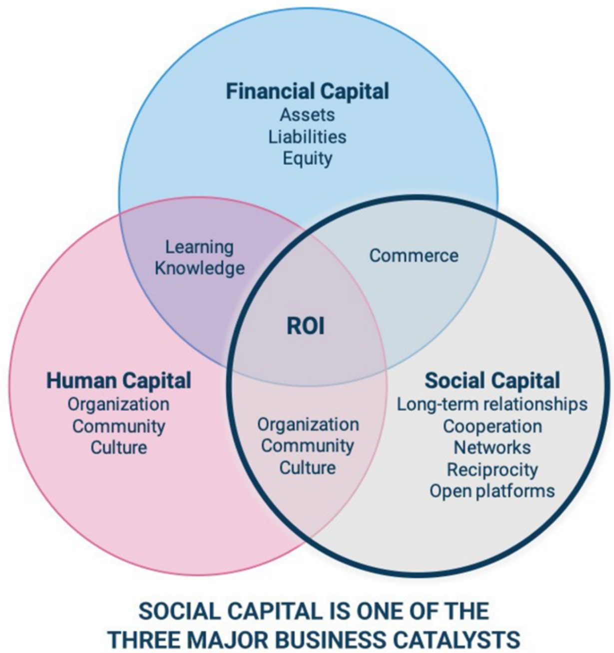
A Review of Social Capital

The concept of social capital is embedded in historical thinkers from Tocqueville, J.S. Mill, Toennies, Durkheim, and Weber (Bankston and Zhou 2002) and was first used as a term by Hanifan (1916); however, a formalized definition has only recently been approached with much debate. Due to the domain particular character of social capital and the intricacy of how it is operationalized, the literature has a wide range of definitions. The parallels of the majority of definitions of social capital are that they concentrate on interpersonal relations that have mutual benefit. The mutual benefit is usually termed in some form of productive use with an intent to move in a specific direction.

The beginnings of social capital research may be found in the works of Coleman and Bourdieu (Gillies et al., 2006), and they are conceptually similar to the economic concepts of financial and human capital (See figure 1, Palter, 2010). Human capital comprises the knowledge and capabilities that enable people to successfully perform their duties (Davidsson & Honig, 2003). Financial capital includes the assets, liabilities, and equity of a business. These can be in the form of physical capital such as facilities or cash (Snell & Dean, 1992).

Figure 2.1

Forms of Capital



(Palter, 2015)

Bourdieu (1986) used the definition of social capital as "the aggregate of actual or potential resources linked to possession of a durable network of more or less institutionalized relationships of mutual acquaintance and recognition, in other words, to membership in a group" in the first systematic contemporary definition that was focused on the community or civic level (p. 2). However, there is an abundant discussion amongst researchers over what represents the social capital domain and its broader pertinency in practically all societal actions (See Table 2.1 for a non-inclusive list). Additionally, every field of study attempts to define it through a context that fits their area of focus (Bellamy, 2015; Kobayashi et al., 2013; Lee et al., 2015; Murayama et al., 2015; Villalonga-Olives & Kawachi, 2015).

Table 2.1

Definitions of Social Capital

Author(s)	Definition	Year
Hanifan	Early description of how social capital 'the tangible substances that count for most in the daily lives of a people, namely, goodwill, fellowship, mutual sympathy and social intercourse among a group of individuals and families who make up a social unit, the rural community, whose logical center is the school'	1916
Bourdieu	'the aggregate of the actual or potential resources which are linked to possession of a durable network of more or less institutionalized relationships of mutual acquaintance or recognition made up of social obligations ('connections'), which is convertible, in certain conditions, into economic capital and may be institutionalized in the form of a title of nobility,	1986
Baker	'a resource that actors derive from specific social structures and then use to pursue their interests; it is created by changes in the relationship among actors'	1990
Coleman	'Social capital is defined by its function. It is not a single entity, but a variety of different entities having two characteristics in common: They all consist of some aspect of social structure, and they facilitate certain actions of individuals who are within the structure'	1990
Burt	'friends, colleagues, and more general contacts through whom you receive opportunities to use your financial and human capital'	1992
Loury	'naturally occurring social relationships among persons which promote or assist the acquisition of skills and traits valued in the marketplace. . . an asset which may be as significant as financial bequests in accounting for the maintenance of inequality in our society'	1992
Putnam	features of social organization such as networks, norms, and social trust that facilitate coordination and cooperation for mutual benefit'	1995
Fukuyama	'Social capital can be defined simply as the existence of a certain set of informal values or norms shared among members of a group that permit cooperation among them'	1997
Nahapiet & Ghoshal	'the sum of the actual and potential resources embedded within, available through, and derived from the network of relationships possessed by an individual or social unit. Social capital thus comprises both the network and the assets that may be mobilized through that network'	1998
Woolcock	'the information, trust, and norms of reciprocity inhering in one's social networks'	1998

Various researchers have characterized it as tangible or intangible assets acquired by agents through associated ties that contribute to improving beneficial conclusions such as execution, attainment, and upholding a competitive lead (Andrikopoulos & Economou, 2015; Bellamy, 2015; Lancee, 2015; Liang et al., 2015; Ou et al., 2015; Villalonga-Olives & Kawachi, 2015) For example, Villalonga-Olives and Kawachi (2015) define social capital as "the resources available to individuals and groups through membership in social networks" (p. 1). According to Ritchie and Robison (2012), "Social capital is a person's or group's sympathy for another person or group" (p. 2).

Alternatively, Coleman (1988, 1990) defines social capital in terms of its purpose: any component of the social structure that can be used as a resource for action by the actor. According to Coleman, these networks have these dimensions: commitments, expectations, and trustworthiness. Coleman also points out that social capital is a community good through government and civic organizations because all members of a social organization share its advantages, not just those who empowered in it. As a result, social capital is frequently generated and extinguished as a by-product or unintentional effect of rational individual behavior. This might result in misalignment between the individual and group optimums, resulting in underinvestment. This realization has two significant implications.

First, people profit directly from social capital if its effects can be limited and appropriated (Dasgupta, 2000). Still, it can also benefit indirectly if it only emerges in the conventional public good form at the aggregate level. Second, social capital can occur as collateral, the unforeseen effect of interaction, or a deliberate, goal-oriented effort. Similar to other forms of capital, social capital is both "appropriable" (Coleman, 1988) and "convertible" (Bourdieu, 1985). This value is interdependent and creates a mutual benefit for both parties.

Social capital, a potential benefit (e.g., resources, information, and expertise), derived from social structure (Wacquant, 2017), can improve individual or community efficiency by allowing coordination (Putnam, 1993). According to Burt (2017), the design of the network in which individuals are working embodies social capital because it affects both the flow of information and the capabilities of network members. Interfirm relationships serve as conduits for the exchange of information and expertise between parties (Galaso, 2021). Because their research topics are typically at the intersection of numerous levels, Capaldo (2007) has urged that social capital researchers adopt social capital network theory, particularly cross-level analysis. The central claim of the social capital literature is that networks of interactions create or lead to resources that can be utilized for individual benefit. The number of collaborative ties, weak or strong, was positively connected to a firm's innovation performance by Shan, Walker, and Kogut (1994). Personal interactions with others, according to Aldrich & Fiol (1994) and Ahuja (2000), are information conduits that develop a model of obligations and goals based on an expectation of a mutual benefit called reciprocity. Reciprocity is the construct whereby individuals contribute, collect, and return (Mauss, 1967), and equitable principles (Koka & Prescott, 2002). The more extensive a person network is, the more instrumental they can be in a collaborative network. Having direct access to contact as opposed to going through brokers, someone with a large network can obtain improved innovation performance (Burt, 2004). Size and diversity of one's personal network are more important than titles in that network. Portes & Landolt's (1996) research shows that even weak ties are more significant due to the ability to bridge between groups. The Internet has amplified this effect and "in the hands of bridging individuals–is a tool for enhancing social relations and information exchange, and for increasing face-to-face interaction, all of which help to build both bonding and bridging social capital in communities" (Kavanaugh et al., 2003, p. 4).

Some research shows that the bigger an individual's social capital, the better their chances of reaching an elevated desired outcome (Chen et al., 2015). Mismanaging social capital can change a profitable social benefit into a disadvantage, just as investments in physical capital are neither costless, revocable, or exchangeable (Gabbay & Leenders, 1999; Gargiulo & Bernassi, 1999; Hansen et al., 1999). Reading a book, listening to music, or watching television alone in one's house does not produce social capital, but sharing a cup of coffee with a colleague or being a member of a sports team can. An individual's social capital can therefore be defined as one's collected network of connections that are lasting, trustworthy, reciprocal, and full of socioeconomic resources, whereas a group's social capital is the integration of individual members' social capitals. It is essential to know whom one is associating with and what time is required to nurture this relationship. It's in our nature to desire to interact with others, and we prefer to form closer bonds with only a few people. It's critical to keep unwelcome and unimportant people out of our life. While we keep our interactions to a bare minimum, we make it a point to cultivate strong bonds with those who are truly essential to us. If we don't, we'll be wasting time or, worse, causing mental discomfort. Regardless, we do not have accessibility to an infinite pool of connection candidates, no matter how much we invest in building our network. This is the result of limited access to alternate network pools because of time zones, cultures, language barriers and lack of scale to process.

Individual and collective assets entrenched in social relations and institutions are defined as social capital by Coleman and Putnam (2000). Putnam's thesis was notable for its argument that social capital might produce both good and bad effects. Lin (1999) used network theory to define social capital as "resources inherent in social networks accessed and utilized by actors for actions" (p. 1), as well as conceiving and measuring it as individual and communal assets. Social capital, in a broad sense, can be defined as the valuable resources that exist within and because of social relationships that offer a mutual benefit.

Social Capital Theory

Social capital theory (SCT) suggests that the accumulation of social capital can lead to other types of capital, such as financial capital, human capital, and psychological capital (Dubos, 2017). In addition to human capital, family background and social capital have also emerged as new and influential factors in determining the level of earning income (Mok & Jiang, 2018). In this context, career aspiring individuals might engage in interaction scenarios primarily to accumulate social capital rather than human capital.

The form and substance of one's social relationships, according to Adler and Kwon (2002), are the foundation of social capital. Its effects are based on the knowledge, guidance, and commonality it provides to the agent. They discovered three elements of social organization, each of which is ingrained in a different type of relationship: market associations, in which goods and services are bartered or substituted for currency; tiered ties, where loyalty to authority is paid in return for monetary and spiritual stability; and social relationships, where favors and gifts are exchanged. The number of resources that can be gathered through long-term, institutionalized social interactions with mutual understanding, acknowledgment, and cooperation was further developed by Bourdieu and Wacquant (1992). According to Palloni et al. (2001), the sociological value of higher education qualifications is not about amassing information but about raising graduates' relative social position. Students are motivated to participate in various social activities and model the value systems, behaviors, and lifestyles of their peers, when exposed to highly educated peers, which grants them membership in various interpersonal networks and ultimately increases their level of social capital (Palloni et al., 2001). Two theoretical models underpin the construct of social capital: one guided by Bourdieu and the other by Coleman and Putnam. Bourdieu (1986) concentrated on different forms of capital in reproducing asymmetrical power interactions. Coleman (1990), conversely, took a more cogent assessment and defined social capital by its utility: "facilitate certain action of individuals who are within the structure" (p. 98). There are three types of social capital, according to Coleman: "(1) obligations and expectations that are based on the social environment's trustworthiness; (2) the ability of information to move through the social structure to offer a basis for action; and (3) the presence of rules" Coleman (1990, p. 99). Coleman and Bourdieu both considered social capital to be a character trait, while Putnam (1993) considers it to be a group trait. The latter thinks that social capital is developed from the collection of ties, customs, and trust that emerge within a group, and that it provides the drive for all members of that group to pursue their common goals. The usage of this concept as a form of capital provoked a variety of debate. Bourdieu (1986) perspective was comparing social capital to economic capital in that it grants a group or individual certain dispensations and cultural capital (e.g., knowledge of humanities, literature, or protocols) distinguishes a group or individual from their less fortunate colleagues, social capital provides the networks and connections that enable sustained and potential access to advantages. Similarly, Putnam (1993) likened social capital as individual relationships to physical capital, as physical goods, and human capital, as unique characteristics. Putnam established his theory of social capital subsequent to Coleman's. His central concept is that social networks contain a benefit, whether in the form of economic or social, for individuals. Like physical and human capital, social contacts impel the productivity of individuals, groups, and organizations. Physical capital is found in material goods, human capital is found in the labor workforce, and social capital is found in interpersonal relationships (Putnam, 2000). Individual relationships through strong and weak ties form social ecosystem that maintains two constructs: reciprocity, and trustworthiness rules (Putnam, 2000). Social capital refers to certain aspects of social life, in particular the social relationships that can provide economic value. They enable participants to work more successfully together to achieve common goals.

In contrast to Putnam's political science perspective and Coleman's sociological perspective, Fukuyama (1995) combines social capital and trust within an economic context. He discovered that the level of trust inherent in each society impacts “its wealth, degree of democracy, and ability to compete economically by comparing the relative economic performance of different nations and cultures based on degrees of trust” (Fukuyama, 1995, p. 25). Alternatively, social capital may be harmful to society (Adler & Kwon, 2002). Agents with access to vital information have an advantage that can be prejudicial, present alternative social norms, and limit access (Portes, 1998). When a social network does not create social good, Halpern (1999) discusses similar downsides of social capital. As a result, social capital may contribute to nepotism, unfairness, and corruption. Mainly when the network is closed, introductions are only made from within the network ecosystem that is biased towards keeping it protected. For the purposes of this research, I will use the definition offered by Putnam (1995), and enhanced by Woolcock (1998), given that he highlights the inherent nature of reciprocity. Combining these concepts, a working definition to use is: relational networks that facilitate coordination trust, and norms of reciprocity.

Levels of Analysis

Reviewing the major approaches to social capital can be done at one or more levels of study, such as macro, meso, and micro, in relation to societal levels (Lewis et al., 2013) (see figure 2, Lewis et al., 2013). The macro-level focuses on the representation of social capital in state and government structures, regulations, and governance that promote the capacity to enable structural, collective community responsiveness.

This interconnectedness can have a power dimension, in which long-term characteristics of the socioeconomic system impart advantages and disadvantages to groups in ways that predispose public officials to prefer some interests over others. (Stone, 1980). Stone is referring to public officeholders being "dependent on the interests of others through overt pressure, financial gains or anticipated reactions" (1980, p. 98).

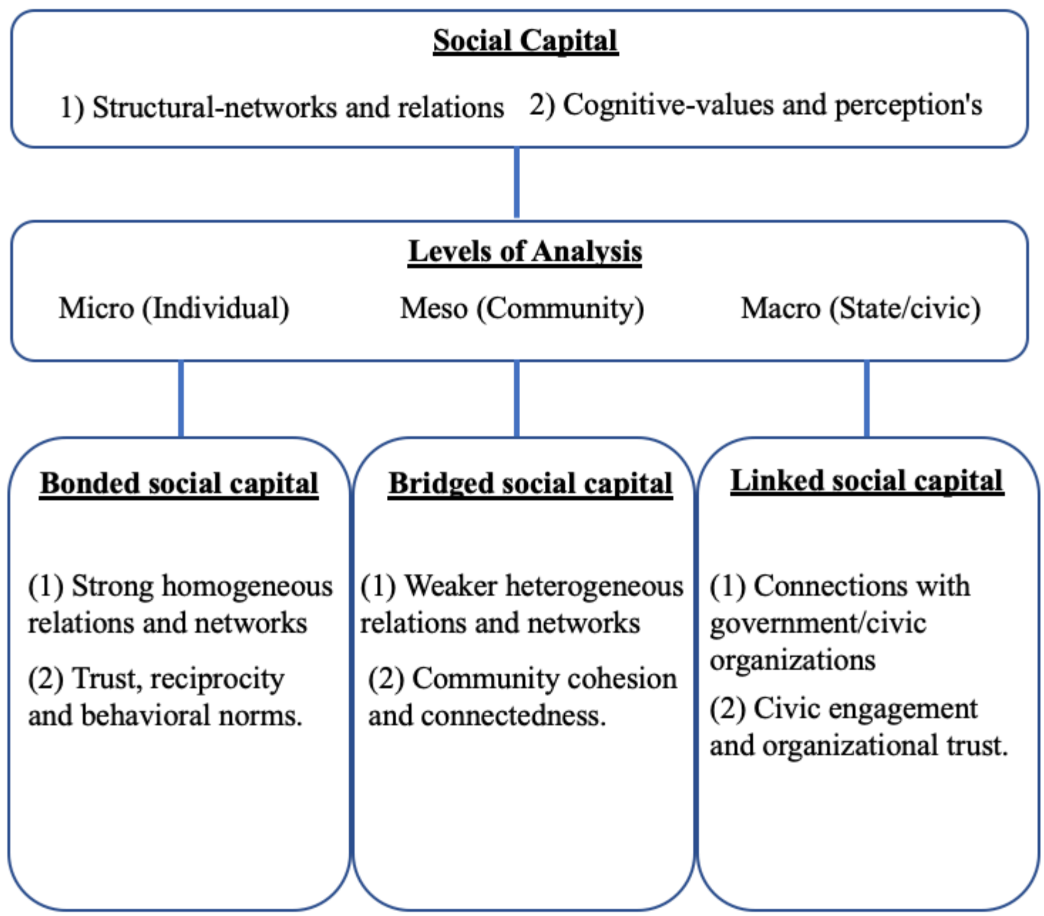
Lobbying, "the art of changing money into policy" (Baumgartner et al., 2009, p. 10), is one of the oldest professions and has been subject to constant criticism for the abuse that it can promote (Gilligan, 1997). The vehicle of choice is to use a concept called ear marking—where policy and funds are directed to a specific project and usually have nothing to do with the main policy or action—and the more salacious term is pork barreling. This approach though once a minor occurrence has been on the rise, costing taxpayers nearly $17B according to Citizens Against Government Waste (2021). Cialdini & Goldstein (2004) have advocated for strong transparency of everything of value, from a lobbyist to a member of congress, and severe penalties for ethical violations.

Finally, micro level elements, which deal with individual behavior, are concerned with the connectivity or linkage of individuals at similar hierarchical levels. Using the micro level as the foundation, and despite having various definitions of social capital, some similarity exists across all definitions with one core central idea that “our social ties matter and bring us benefits” (Neves, & Fonseca, 2015, p. 4). This definition was extended to include “the manner in which networks and their emergent properties (e.g., trust and norms) can constitute a resource for their members” (Crossley, 2008, p. 477). All these varying contexts of the definition were an extension of Lin’s (2001) two basic agreed-upon tenants – “its embeddedness in a structure of social relations and the fact that it provides actors with access to valuable and scarce resources that contribute to their well-being” (p. 14). Lin (2001) extended this fundamental concept of social capital as an “investment in social interactions with an expectation of return. Individuals interrelate and network to generate benefits” (p. 14). For this research, we will use the idea of social ties that bring us benefits, with an expectation of return, and will focus on the micro-level of analysis with individuals.

The resources embedded in one's network or affiliations make up social capital. The economic value is a connection that is willing to provide a benefit and the benefit may be of higher value due to the willingness of the connection and their relative hierarchical position. A position of power could be a high-ranking job in a particular business or corporation, or it could be a domain area that provides advice. It is not enough to simply be in this position; the connection must also be prepared to assist. Inclination to help could be in the construct of altruism or mutual advantage. The assumption of reciprocity or compensation is one aspect of the utilization of social capital.

Figure 2.2

Levels of Analysis in Social Capital



(Lewis et al., 2013, p. 94.)

Corporate Use

Given the wide applicant pool, employers recognize the value of social capital; social relationships can assist in discovering qualified applicants who match an employer's needs. External contacts can aid in the identification of qualified candidates, which can be a considerable benefit to the organization. If a company or organization has the wrong kind of social capital, it might suffer internal relationships from too inward-looking colleagues who fail to consider external events or resources (Granovetter, 1973). When it comes to job hunting, networking is the most effective strategy (Batistic & Tymon, 2017). Regardless, the fundamental goal of networking is to obtain information, advice, and connections that can lead to interviews and job offers. According to research on organizations, specific contact patterns encourage the creation of social ties that are purposeful in an effort to build social relationships among participants (Shoji et al., 2014). discovered that particular routines and behaviors, such as one-on-one and group tête-à-têtes, enabled the types of interactions most likely to result in tie formation in their research of an intervention aimed at enhancing Latinx parents' school-based social capital.

Best practices in social capital are to ensure diversity of connections and reach a large ecosystem of contacts that may have influence. Stronger social capital networks are dependent on diverse players and connections. Research finds that the more diverse a team or social network is, the more capable it is (Johnson et al., 2018; Lauring et al., 2019). Diversity is critical in a social capital network (Lin, 1999). Individuals in close-knit populations, such as some immigrant groups, have strong social ties, depending on affiliates of their ethnic group for furtherance. Simultaneously, their lack of outside social contacts may make them perpetual outsiders in a larger society, preventing them from progressing economically. Social independence can occur in either direction. For instance, a close-knit group may isolate themselves, but the greater community may avoid them as well. An example of this is the Amish community who historically have isolated themselves from the outside community and have had less access to opportunities to innovate. It may prove to be harder to build a diverse social capital network without some external network to prospect. The importance of social capital in a corporate environment is largely dependent on the individual employees and their ability to grow their personal social capital (Johnson et al., 2018). In this context, this research will focus on the micro level of analysis for social capital.

Dimensions of Social Capital

There are three core dimensions to social capital (Nahapiet & Ghoshal, 1998), and each have elements that define its differences (Vallejos, 2008). The distinction builds on Granovetter's (1992) research on structural and relational integration. It is consistent with the widely held belief that social capital is made up of features of social structure and the nature of social connections known as norms. The existence of network linkages (e.g., who knows who) as well as roles, regulations, and processes are all indicators of structural social capital. Because social ties and structures are necessary for social trade, the structural dimension can be seen as a predecessor to both relational and cognitive dimensions (Tsai & Ghoshal 1998). The relational dimension differs from the structural dimension in that it is intangible because it encompasses the ideas of people and they think and feel, whereas the cognitive dimension comprises social norms. The literature frequently refers to two dimensions: structural and cognitive, for example (van Bastelaer, 2001; Chou, 2006; Grootaert et al., 2003; Krishna & Shrader, 1999; Uphoff, 1999). Since around 2004, references to the three dimensions— relational, cognitive, and structural —have become considerably more prominent, and this is currently the most widely used and putative framework.

Table 2.2

Dimensions of Social Capital

Dimension	Features (Nahapiet & Ghoshal, 1998)	Elements (Vallejos, 2008).
Structural	Connection patterns: network settings, density, connectivity, and hierarchy	Ties Stability Density Setting Connectivity
Relational	Assets that are created through leveraged relationships that include rules, trust, obligations, and expectations	Trust Reciprocity Participation Obligation Diversity of tolerance
Cognitive	Resources that represent a shared vison and meaning of systems such as language, symbols, codes, and narratives	Values Shared narratives Shared language Culture Codes

Social capital theory establishes norms for behavior through processes like completing a job search that often results in the ability to conduct a faster job-search activity (Auslander & Litwin, 1988, 1991). Social networks enhance the activity by providing knowledge and opportunities relevant to job options. Social networks provide a link to social capital which comprises ties of trusting relationships between network connections cooperating throughout explicit, prescribed, or institutionalized influence levels in society (Szreter & Woolcock, 2004). Access to target positioned contacts and information is essential in securing the desired job. Those with "extensive professional networks have been shown to have better employment opportunities" (Batistic & Tymon, 2017, p. 1) from an establish a mutually trusted interaction that is an underlying contractual agreement that serves a mutual benefit. For this research, the focus will be on the relational dimension that includes the constructs of reciprocity and trust.

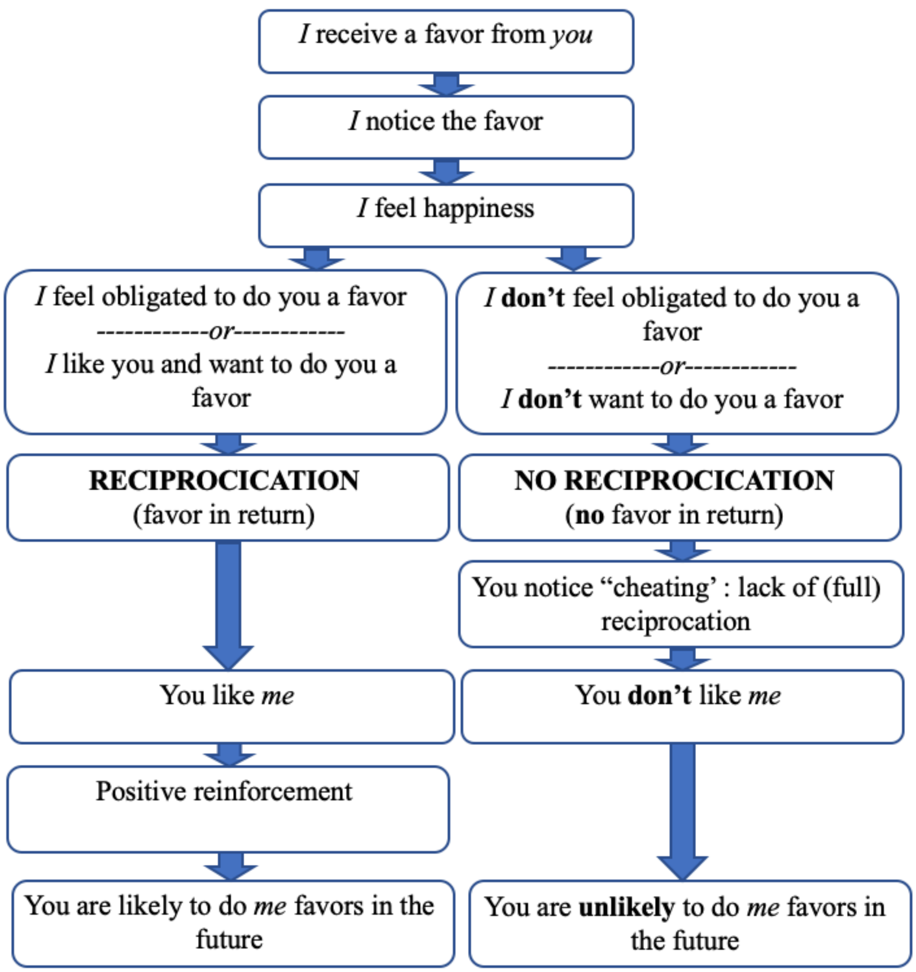
Reciprocity

Social capital theory defines this mutual benefit as reciprocity (Gouldner, 1960), and this is a general, basic inclination that can be located in most cultures throughout history. Reciprocity is critical in building the ties that create cohesive relationships that form social capital. In most studies (Axelrod, 1984; Friedman, 1971; Fudenberg & Tirole, 1991; Kreps et al., 1982), reciprocity has been defined as a strategy relevant to recurring interactions, where the actors use reciprocating methods that are mutual in the short term, but self-interest directed in the longer term. People have reciprocal behavior if they reward favorable actions and punish unfavorable ones.

Reciprocity has been examined in various societies, and humans have a natural desire to connect with other humans, which is best satisfied through gift exchanges. This is referred to as the psychological sense (Levi-Straus, 1969), which they define as “feelings of moral obligation implied by a gift and that those feeling lead to patterns of reciprocity in gift exchange” (p. 301).

Figure 2.3

Reciprocity Relational Approach



(Trivers, 1971, p. 51)

When two people meet, the capacity to form a bond is contingent on both parties reciprocating equally in a dialogue (Collins & Miller, 1994; Sprecher et al., 2013). This suggests that an interaction in which one side does not reciprocate is less likely to succeed (Sprecher et al., 2013). People are more drawn to those who give them knowledge or get information from them (Collins & Miller, 1994). Reciprocity is the concept that every time someone gives it includes an implied request to return what, value aside, has been given, and hence it necessitates reciprocity. Reciprocity can be defined as a social dynamic in which people give, receive, and return; reciprocity is used to change a stranger into a personal relationship in the paradigm "I give so that you may give" (Mauss, 1967, p. 4). This is the gift's strength and efficacy: receiving from others entails a strict commitment to give back, to repay what has been received. This is sometimes referred to as a “quid pro quo” or “vice-versa” (Sahlins, 1965, p. 203). Sahlins suggests that the social relationship between persons determines the nature of reciprocity between them. In anthropology, the idea of reciprocity has been chastised for being poorly defined and so insufficiently "stable" to allow for comparison (MacCormack, 1976). A seminal experiment by sociologist Phillip Kunz (1976) showed the power of reciprocity with strangers. Kunz mailed out Christmas cards to 600 random strangers, including a personal note and a photograph of his family. The response rate was nearly 35% since the recipients felt he had done something for them; they felt obligated to return the favor.

Gift-giving offers a gesture, whereby the other party may be indebted. This norm contributes to social stability by serving as a beginning point for forming interactions between two individuals or groups of individuals. If both parties agree that accepting a gift obligates them to repay it, a natural and initial antagonism can be overcome (Goldner, 1960). In Durkheim's book *Morals and Modernity* (2002), he notes that the idea of society being produced due to moral obligation—not just material interest—is foundational to the concept of reciprocity.

There are various scenarios where it is reasonable to suppose that the level of support people receive and the extent to which support exchanges are reciprocal are significant. Giving more than one receives, for example, can lead to sentiments of exploitation, unfairness, and resentment, as well as a general sense of being taken advantage of. On the other hand, giving too little might lead to emotions of remorse or shame (DiMatteo & Hays, 1986; Homans, 1961). In addition, a lack of reciprocity encourages power imbalances in relationships, which can lead to emotions of dependency and the breakup of a partnership (Blau 1963; Johnson, 1988). Reciprocity is regarded as a sign of the highest level of intimacy in a relationship (Levinger, 1974). As a result, it is not surprising that a lack of balance of support, whether it's more giving or more receiving, is linked to lower levels of happiness (Walster et al., 1978).

Reciprocal altruism researched by Bob Trivers (1971). Trivers is a social biologist whose research focused on "cleaning symbiosis, or the partnership relationship between cleaner fish and their hosts. The host fish allows the cleaning fish free entrance and exit and does not eat the cleaner one, even after the cleaning is done" (Trivers, 1971, p. 2). Trivers proposed that altruism—"defined as an act of helping another individual while incurring some cost for this act"—could have evolved. "It might be beneficial to incur this cost if there is a chance of being in a reverse situation where the individual who was helped before may perform an altruistic act towards the individual who helped them initially" (p. 37). This could be explored using the ethical dilemma as demonstrated by the Prisoner's dilemma (Flood & Dreshner, 1950). Using a repeated strategy would be a means to cooperate unconditionally and successfully in the first place and behave cooperatively (altruistically) if the other prisoner does as well. This type of altruism can propagate within a society if the odds of meeting another reciprocal altruist are likely, or if the game is repeated at length (Flood & Dreshner, 1950). Human reciprocal altruism would be evident in scenarios that include the following behaviors (but is not limited to): helping car accident survivors, giving charitable donations beyond the tax relief level, or driving courteously. In his late career, Samuel Johnson (1756) has been credited with writing, "The true measure of a man is how he treats someone who can do him absolutely no good" (as cited in "The true measure", n.d.). Adam Grant's (2013) research focused on this altruism and resulted in his book *Give and Take,* in which Adam notes: "The more I help out, the more successful I become. But I measure success in what it has done for the people around me. That is the real accolade" (p. 5).

Alternatively, indirect reciprocity occurs when humans cooperate with strangers to gain brand reputation (also referred to as an "image score"). This can lead to the subsequent payoff from humans who cooperate with those with high reputations or hierarchical positions. Because of the accessibility indirect reciprocity provides to more places, an individual occupying a more elevated position also has a more excellent command of social capital (Lin, 2001). Reciprocity is not limited to humans; recent advancements in AI-driven IPAs abilities included expressing emotional responses by imitating human speech intonations, making them seem more "human" (Schwartz, 2019). According to the Social Response Theory (SRT; Nass & Moon, 2000), the presence of reciprocity is important to interactions between humans and machines. (Cerekovic et al., 2017), with users not just interacting but building relationships with the technology (Han & Yang, 2018; Schweitzer et al., 2019).

This reward and punishment system has been around since the early foundations of societies. Archaic gift-giving represented the collective actives of exchange through which societies were able to reproduce beyond the resources they had available to themselves (Adloff & Mau, 2006). These exchanges create links in the form of social contracts that can reduce mistrust, produce social ties, foster alliances, and prevent wars between clans (Bourdieu, 1986). Reciprocity was helpful at the clan level to reduce friction, but it also offered the opportunity to build social ties that created connective bonds between individuals. Though a significant amount of research has been done at the society level (Coleman, 1988; Burt, 2017; Dubos, 2017; Durlauf & Fafchamps, 2004; Putnam, 2000), this research will focus on the individual perspective of interpersonal reciprocity and the relationship building and trust associated with this.

Significant research denotes that interpersonal reciprocity is an important construct of human behavior. This is the gift's strength and efficacy: receiving from others entails a strict yes informal contract to give back, to repay the value of what was received. One way to gain access to items of interest or needs is to have them circulate through people in the form of reciprocity. Bartering is one form of reciprocity that is a way to develop a personal relationship and gain something one needs but cannot obtain on their own. This alludes to the notion that a shared offering symbolizes the person who provides it and the interpersonal relationship with the recipient, aside from its animistic connotation (Putnam, 2000). Reciprocity is thus an exchange of presents or material, or it is a symbol representation of the exchange. This exchange necessitates reciprocation and refusing a sentiment could be viewed as an insult (Fehr et al., 1993). Because what is bartered is inalienable from people who trade and the unique relationship developed, reciprocity transcends economic transaction without eliminating it. The conversion of an unfamiliar person into a respective relationship is carried out through reciprocity and is based on the principle of *do ut des* ("I give so that you may give back") (Burkert: 2000, p. 302). Some do keep strict accounts of any favor they've done. This will be ultimately evident when, at a later point, an individual in a previous transaction that is owed a favor will require payment in the form of their wish or desire. Of course, one has the right to refuse the request, but they do so at the cost of the relationship and future reciprocal opportunities. No explicit agreement was ever made with the other person, and they may show up to collect at any time, which can make reciprocity very stressful (Ciairano et al., 2007).

Research underscoring the omnipresence of reciprocal behavior are in several domains including psychology and economics, as well as a growing list of literature in anthropology, sociology, and ethnology (Kahneman et al., 1986; Fehr & Gächter, 2000). Thaler (1988) highlights that low offers in an ultimatum game are frequently rejected, and if the subjects are given the ability to sanction a party based on actions, subjects often sanction defectors, even at the cost to themselves (Fehr et al., 1993). Reciprocal actions are typically modeled based on an interactive reaction to an act that is either recognized as positive or negative, and although reciprocity could decay, it is not always in the immediate outcome space (Brandts & Sola, 2001). Reciprocity comes in three distinct forms. It can be balanced, generalized, or negative. Generalized reciprocity refers to an interaction that has no inherent value or an expectation of timely repayment of the goods or services, and it is often used to break the ice in hopes of a mutually successful outcome (Putnam, 1993). This is common when ambassadors exchange gifts when first meeting. It is also most known as the altruistic form of reciprocity; although, that may not be an accurate phrase, given that reciprocity is the expectation of a reciprocal benefit, as opposed to a gift.

The deeper form of reciprocity is called balanced (Putnam, 1993). Balanced reciprocity starts with a perceived value and has some form of expectation of repayment terms including a timeline (Putnam, 1993). Time frames are indeterminant, but the strength of the need to meet the reciprocal exchange will decay over time. For instance, a favor you did for a colleague over 10 years ago will not have the same value as a more recent occurrence.

Lastly is the construct of generalized reciprocity where there is always an imbalance of long-term interactions (Putnam, 1993) for instance people tend to be helpful without the formal expectation of a return, but they may keep a collective bucket of I owe yous. The patterns of generalized reciprocity lead to trusting actions in conditions people would not typically embraced (Putnam, 2000). For instance, the act of holding the door for someone creates a level of trust between the two individuals, even if it is not warranted. Relationships are defined by two key characteristics: presence and contribution (Halpern, 1999). A relationship typically is initiated within immediate sight between the two parties. Therefore, it is hard to ignore someone's presence without offering something in return, such as a greeting, a wave, or some other acknowledgment that the other is present (as in when a stranger enters an empty elevator). Giving something implies making oneself known, and whoever is present always provides something, even if it is just their presence. Therefore, it is more challenging to refuse a favor when asked in person. People have a difficult time saying no if the ask is straightforward enough (Gladwell, 2019). The easiest way to avoid the need for presence and contribution is to avoid contact with others one does not wish to associate with to avoid uncomfortable situations. AI does not conform to this generalized reciprocity since it has no expectation of acknowledgment or maintain an account of what is owed. It is task driven and operates as a service to deliver on what the interacting party requires.

Negative reciprocity is a type of reciprocity in which one of the parties to the trade tries to get more out of it than the other. Reciprocity isn't always a fair trade, which can lead to misalignment or even abuse. For instance, during a geographic crisis moment, vendors could increase the price of their goods to achieve a higher margin without any reciprocal benefit, as was the case in with price gouging during 2016 hurricane Matthew in Florida. Water that is usually $1 a bottle had a hurricane special price of $5 a bottle (Beatty et al., 2021). The core construct to negative reciprocity is that it has an element of predatory motives built in (Putnam, 1993), so standard supply and demand would not be considered predatory, such as the Uber price surges, although debates remain. Negative reciprocity can have a substantial impact on goodwill established by the vendor. This goodwill can be earned or destroyed.

Reciprocity can take on a dimensional approach and build worth through reputation and experience. People are generally eager to do a proportionately larger favor after someone has done something modest for them, according to research (Comello et al., 2016). Participating in that first reciprocal conversation can increase one’s chances of responding to subsequent, often larger, requests in the future. This is known as the "foot-in-the-door" strategy in marketing (Freedman et al., 1966). Someone starts with a minor request, and if you agree, they go on to a much larger request. Alternatively, another strategy known as the "door-in-the-face" technique might be applied to take advantage of reciprocity (Freedman et al., 1966). The persuader begins by requesting a huge favor that they know you will refuse. They then appear to concede by requesting a much smaller favor, which you may feel forced to perform. The reciprocity rule may be a fundamental human habit (Gouldner, 1960). The rate at which disclosure and reciprocity take place is determined by the relationship's status. Either way, the idea is to build the favor bank to cash in at a future point or be obligated to pay out when one requests.

Since it is implied in a reciprocal relationship that some form of reciprocity exists, could there be situations presented where one party makes a predetermined decision based on the implied reciprocity? This would be tough to do in a human-to-human interaction, but if one of the parties had no expectation of reciprocity, would the other party be more inclined to interact with this non-confirming party? Could the advent of technology—which is capable of sourcing appropriate social capital connections without the need for reciprocity—be of interest to individuals looking to manage their bank of favor and debt obligations? Could this be done through AI that also presents the unlimited scale of capability? Some shifts in today's events have made the appetite for use of technology more relevant (Legris et al., 2003), and world events have forced many to leverage technology where they historically would not have (Caselli & Fracasso, 2022).

Pandemic

Research suggests that in-person interactions are preferred methods of building one's social capital network (Caughlin & Sharabi, 2013; Ramirez & Wang, 2008). In-person interactions offer the ability to read physical and verbal cues from others, which have been learned from early childhood about others' truthfulness and intentions (Dimitrius et al., 2008). Additionally, people formulate strategies for ascertaining whether to proceed with an interaction with a specific person. Things changed with the pandemic, and communications are more efficient through better technology and fewer boundaries; it is far more difficult for one to meet those who could enhance their social-capital network consistently. To reduce the spread of the pandemic, social distancing and seclusion have been widely encouraged.

The COVID-19 epidemic has hampered face-to-face contact with intimate friends. A study during COVID looked at how professionals when compared to pre-COVID times in Hong Kong's finance region and how they modified to earlier techniques of social interactions and the tangible outputs suggested that they had created either “no new professional acquaintances or a significantly reduced number of new professional acquaintances” (Militello, 2021, p. 14). The social distancing strategy implemented to reduce the spread of the virus had a negative effect on social interactions (Bond, 2021).

These challenges stimulated rapid use of non-face-to-face technology, beyond the telephone, text messages, and email. These traditional communication methods were limited by a person’s capability to infer intentions and to establish trust by using facial cues (Chawla, 2020). This led to online video conferencing rapidly exploding. These technologies provided the ability to measure visual cues; however, this was still limiting in terms of access to contacts outside one’s immediate sphere, and as a result, many invested more effort on the already in-use social networking platforms, such as LinkedIn and Facebook (Almarzooq et al., 2020).

However, there were limitations to these technologies. Strengthening acquaintances through establishing a professional, trusted connection in an expedient manner would most likely require a trusted reference from a known connection (Claybaugh & Haseman, 2013). Although these references may not always be apparent for what they are, for example, and sometimes people are not doing you a favor. Instead, they are proposing a deal, but they do not say it openly. On the contrary, they make their help look like generosity. This approach is not new; however, these phishing scams (“COVID-19 kit,” “Coronavirus package,” or Medicare benefits related to the virus) significantly increased during the pandemic (Ahmad et al., 2020; Etheredge et al., 2021).

Artificial Intelligence

“The final invention by the human race will be AI, as AI will do all the inventing going forward” -James Barret

Concurrent to limitations on contact, due the pandemic, technology is also rapidly changing. Technology serves society in many capacities, from engineering accomplishments (Hadron Collider) to the mobile phone with mapping technology (Google maps). It has many intrinsic capabilities, and one that has been very powerful for society is the great equalizer. It shows less and less bias towards the users (Lin, 2021), and it is altruistic in nature and is evolving to be a trusted companion (Wu & Huang, 2021). The best future technology will resemble people from the ability to rapidly process information to comprehending and interacting with the environment including humans (Bostrom, 2017). “Automation, sensor technologies, computer vision, voice, facial recognition, and other sectors will continue to progress, blurring the line between human and machine capabilities” (Bostrom, 2017, p. 15). AI is at the forefront of this rapid advancement and will continue to evolve as more investments and capabilities are exposed.

AI is the highest form of technology that is leveraging computers and data to perform a task or an ability. Unfortunately, the use of the AI term has suffered some degree of marketing abuse, since the product advertised is not really leveraging AI but actually a more basic form of compute technology. The trend can be seen in all forms of marketing and branding. “Inspirobot” for example brands itself as “an artificial intelligence dedicated to generating unlimited amounts of unique inspirational quotes” (Osman, 2019, p. 7). The bot only organizes a background image and fills areas with random, repeatedly perplexing words. At the basic level, there is robotic process automation, which is a process that provides for the configuration of multiple scripts to activate code in an automated process (Osman, 2019). This is frequently confused with machine learning, which employs structured and in some cases, semi-structured historical data to learn and offers predictions without running automated scripts. Machine learning falls short of AI's capabilities because it is limited to predefined knowledge data sets, whereas AI can develop new algorithms and leverage neural logic to present novel approaches (Kaplan & Haenlein, 2019).

Early uses of AI were constrained by a number of technical factors, including available processing technology, data availability, and the machines' still nascent limited adaptability. They were also influenced by readers’ limited imaginations, which largely left artificial intelligence to the world of science fiction. AI started in its simplest form as calculators, or small, computerized units that could perform arithmetic functions based on instructions given by the operator. AI refers to “a system’s ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" (Kaplan & Haenlein, 2019, p. 24). AI boosts the quality and efficiency of operations and platforms in a variety of sectors, including transportation, energy, health, and education when the machine's ability to mimic intelligent human behavior is high. AI is a primary driver of the fourth industrial revolution – the development of new capabilities that connect the biological, digital, and physical environments. Early forecasts that a computer will prove complex mathematical theorems and even become a chess champion were correct; however, it took 4 decades instead of the 1 predicted (Russell et al., 2010). Virtual bots that have AI incorporated have been on the market for over 25 years, yet have had limited success due to limited capacity and being hard to use (Fluss, 2017). AI has advanced significantly in the past decade due to the availability of data and processing power and will continue to have a growing impact on all areas of the economy and society in the coming years (Skilton, 2017). AI has the potential to have a profound effect on all domains (physical, digital, and biological) and transform virtually every aspect of society (Schwab, 2016).

Today, AI has evolved into an anthropomorphic form of an intelligent personal assistant (IPA), such as Siri, Alexa, and Nest, that is integrating into every facet of daily life. The term AI was coined in 1956 at a conference at Dartmouth, but it is only in the past decade that substantive development has been advanced. In its formal definition, AI is the pursuit of performing human-based tasks such as outcome prediction, pattern recognition, and complex decision-making through data sourcing. AI agents have two core dimensions – embodiment and presence (Tung & Law, 2017).

The term "presence" refers to the AI having a virtual presence (e.g., Siri) or a visible physical incarnation to guests. The latter has significant anthropomorphism challenges (Gursoy et al., 2019)—the likeness to a real human—and although it can be compelling in design, it is subjected to the uncanny valley effect (Mori, 1970), where unless the embodiment is a perfect human, imperfections and all, humans can revolt against the AI (MacDorman, 2006). For this study, we will avoid the embodiment part of AI and focus on the presence dimension and on the building of trust in the AI for complex tasks.

The revolution and evolution of machines are at a critical inflection point. We depend on AI -driven IPAs like Amazon's Alexa to answer more of our daily inquiries and execute more complex tasks than ever before, as they grow more pervasive in our daily lives (Lopatovska & Williams, 2018). The widespread use of AI technology and its anthropomorphic features have influenced how people view and interact with technology. When using computers or mobile devices, it is uncommon to refer to them as "he" or "she." However, personification arises with IPAs on these devices, such as Alexa and Siri; even though IPAs lack any human physical characteristics, the personified voice is sufficient for users to create a deeper bond (Han & Yang, 2018; Novak & Hoffman, 2019; Schweitzer et al., 2019). IPAs are becoming the lead modality for AI to interact with humans due to their human like qualities and perceived existence to serve, as opposed to sell or market. This has impacted the growth market for AI-driven IPAs, with over 4 billion voice-activated assistants used worldwide in the past year (Statista, 2020).

There is a growth in transparency and seamless integration of technology to the point of unawareness of these assistants (Wheeler, 2019), and a substantial amount of research is looking into how humans engage with them. AI is a technological concept that has applications in operational management, philosophy, humanities, statistics, mathematics, computer science, and social sciences. AI tries to develop computers or machines that can perform tasks that otherwise require human intelligence. Machine learning is a sub-discipline of AI that leads to statistical learning. AI is an area of computer science that enables machines to replicate human intelligence and perform jobs more effectively than humans. In comparison to previous generations of information technology, AI is capable of self-learning and self-updating via data. The learning input is data (which may include text, audio, and video) that may be contextual or non-contextual. AI learns from data using a variety of computational approaches, with adversarial networks and deep learning neural networks being particularly prevalent today.

Senior citizens will gain significant value from AI in the form of timely advice and conversational interaction. The AI will build a knowledge base of the user and use this data to constantly improve the interaction. This could be expanded to include personal introductions to like-minded seniors in order to facilitate collaborative, humanistic tête-à-têtes with the AI-driven IPA serving as the broker. As a result of its interactions with its users, AI has already developed relationships with humans (e.g., www.replika.ai). However human interaction may not be easily replaced by AI, participants who envisioned themselves as medical patients preferred a doctor's interaction and subjective diagnosis over AI, even if the participants were told the AI is more accurate (Promberger & Baron, 2006).

Although still nascent and in pocket areas, career aspiring individuals will soon be able to leverage AI to review non-standardized data queries on values and quality contextual (specific to the user) data in the social ecosystem (Klamma et al., 2020). There is potential for AI to be programmed to maximize opportunities for engagement or seek mentoring opportunities that will result in immediate value to the bottom line of any individual. There are many facets of the AI research that are taking place, from Reinforcement learning processes (Littman, 2015), science, technology, and the future of small autonomous drones (Floreano, 2015), to the ethics of robots with regard to humans (Russell, 2015). It will achieve these through patterns and algorithms that are contextual to the organization and the business environment. Given that it will have almost unlimited access to internal corporate data and the economy at large, the AI system will become an indispensable advisor for management teams. This can be extended to one's personal network of business relations.

Today, this requires the intervention of a programmer and an analyst to verify the validity of the data. Still, tomorrow it will bring consistency and reliability of data analysis to the extent that no human intervention will be required. While the human brain will focus on the most obvious correlations, AI will have the ability to rapidly analyze oceans of information through scenarios and test out all potential outcomes. The quality of an AI system is judged by how well the AI's actions meet specified conditions independently on a set of research observations. This is foundational to the concept of future AI in that AI should be able to comprehend the world it is in and act on it. There is extensive research and ongoing development around AI today, and there should be.

The present-day continuum of human existence is possibly the most exciting period in history. There are great opportunities to use AI to dig through massive amounts of data and present different options based on the data parsed and the algorithms that have been embedded. The forefront of these opportunities will be tedious tasks and require a significant amount of time to process and cycle through patterns and data. Still, eventually, we will see AI present business scenarios for executives to act or not act on (Nevile, 2017).

Presenting of AI data has taken many forms with iconic robots (e.g., C3PO, Terminator) to intelligent voice platforms (Hal 2000, Jarvis), with the latter taking a substantial role in the personal consumer market using IPAs. IPAs are Internet-connected devices that assist their users on a daily basis with technical, administrative, and social tasks, such as tracking workouts, playing music, and interacting with other users (Han & Yang, 2018; Santos et al., 2016). While IPAs started on mobile devices (e.g., Apple Siri and Google Now) there has been a strong push to deploy IPAs in the household environment (e.g., Amazon Alexa). This has grown rapidly due to the advancements of IPAs with natural language processing that enables the IPAs to engage in conversational style communication that can respond to initial verbal inquires but can ask follow-up questions for clarification (Hoy, 2018). IPAs are being used as conduits for online shopping, education, and control of other innovative applications and devices, as well as for communication and camaraderie (Guzman, 2019; Schweitzer et al., 2019). This functionality serves as an antecedent to evaluating how users develop trust in the IPA and if the perspective is functional or relational.

Professor Patrick Lin (2013) points out that “algorithms cannot make an instinctive but bad split-second decision the way humans can, and thus the threshold for liability may be higher” (p. 10). Human decision-makers can make instinctive and ill-advised decisions yet have built trust due to their understated interactive communication capabilities. Interpersonal communication abilities (e.g., adaptability, empathy, acknowledgment, and encouragement) are at the center of human capability over AI (Deloitte, 2017; Deming, 2017).

“As AI technologies advance, they will perform numerous tasks formerly performed only by humans and complement (and even outperform) people” (McKinsey Global Institute, 2018, p. 2). For example, AI can understand questions and respond to them in natural communication dialogues better than untrained employees (Luo et al., 2019). Furthermore, AI can realistically manage data-intensive activities, such as language translation and item suggestions in e-commerce environments (Brynjolfsson et al., 2019; Sun et al., 2019).

The most notable pioneer in the ethics of the AI field is Nick Bostrom. His book *Superintelligence* (2014) led the way for discussions around the capability of AI and how it should be regulated. There are a few sections devoted to the ethical structure of AI and whether society is in danger of AI. It is worth noting that a conscious AI might be less dangerous than a non-conscious one because, at least in humans, affective empathy would put the brakes on immoral behavior. If an AI system has consciousness (sentient), it may care more about individual people than humanity. A perfect example of this is the paper clip scenario (Guerra, 2021), where AI starts building paperclips to serve society and then objectively evolves into the notion that if people did not exist, then society would be better off (e.g., less carbon emissions, less violence etc.). We are a long way off from a sentient level AI, known as artificial general intelligence (AGI), due to the complexities in AI being able to explore scenarios that are not algorithm driven (Marcus & Davis 2019).

According to Lazarus (1991, p. 352) "during the primary evaluation phase, a respondent's assessment of technology is influenced by their social group norms (societal norms), motivation (hedonic), and degree of anthropomorphism (human cues)". Today, the acceptance of technology is becoming more prevalent (Marcus & Davis 2019) due to its usability and is relevant and consistent with social networks and personal norms. As technology evolves, through the capability of AI, the trust and interaction level will increase.

AI is the next industrial revolution that our Global society will experience. It will impact jobs (MacDorman, 2006), healthcare (Promberger & Baron, 2006), safety (Saxena Cheriton, 2020) and what was taken for standard practices and shifting to a new paradigm (Marcus & Davis 2019). AI does this by a set of algorithms and access to ever increasing data sets. This has resulted in new areas that were once considered unapproachable, for example, AI as a painter of art. A recent painting by an AI system sold at an auction for $432k (Cetinic & She, 2022). An AI system, embedded into a robot form factor named Sophia, is also recognized as a citizen of a country with full rights and sovereignty (Parviainen & Coeckelbergh, 2021). Given these paradigm shifts, it is only a matter of time where AI effectively labels sources of social capital.

Trust

Trust is an elusive concept that is a "multifaceted construct that is an essential aspect of interpersonal relationships" (Simpson, 2007, p. 78). Trust forms the guiding behavior for making decisions when social norms or cognitive resources are not available or unreliable for informed decisions (Thagard, 2018). Trust provides security in human-to-human interactions and affects our relationships and decreases inhibitions and defensiveness (Larzelere & Huston, 1980). Mayer et al., (1995) offers the most generally accepted explanation of trust in that they define it as the "willingness of a party to be vulnerable to the actions of another based on the expectation that the other will perform a particular action important to the trustor" (p. 710).

This was expanded to include societal cues (taken-for-grantedness) (Holzner, 1973; Zucker, 1986), or the "expectation of the persistence and fulfillment of the natural and the moral orders" (Barber, 1983, p. 3). Barber (1983) builds on the need to separate that there are two types of trust. One is the "expectation that partners in interactions will carry out their fiduciary obligations and responsibilities, that is their duties in certain situations to place others' interest before their own" and the other is "expectation of technically competent role performance from those involve with us in social relationships and systems" (Barber, 1983 p. 125). One provides a belief of a party's capability, while the other is a belief of a party's intent and goodwill. There are many contexts to trust, from general trust and knowledge-based trust, to interpersonal trust.

Several perspectives have been taken on the different types of trust. Theory about trust has had authors classifying trust either by level of analysis (Lane, 1998; Zaheer et al., 1998) or by the basis for why one trusts (McAllister, 1995; Nooteboom, 2002). Several levels of analysis can be classified. First there is institutional trust, one where the institution acts as the source (Lane, 1998), and it exists when people rely "on formal, socially produced and legitimate structures which guarantee trust" (p. 4). Then, there is the trust in an abstract called system trust (Lane, 1998), which can be trust in both the object and the source of the trust. Lastly, there is interpersonal trust, which Lane (1998) defined as "trust between individuals based on familiarity or derived from membership in a group" (p. 4). For instance, a fellow alumnus of a person's school may have a pre-given level of trust based on this membership as an alum. Interpersonal trust is the primary construct of social situations that require some form of cooperation (Johnson-George & Swap, 1982). This perception that one has that other people will not do anything that will harm their interests results in the opening up to accept risk (Rotenberg et al., 2005). Rotenberg et al., (2005) breaks interpersonal trust into three foundational sections:

> emotional (which refers to the reliance on others to refrain from causing emotional harm, such as being receptive to disclosures and maintaining the confidentiality of them refraining from criticism); reliability (which refers to the fulfillment of word or promise and refraining from scenarios that may elicit embarrassment; and honesty (this refers to stating the truth and acting in ways that are led by good intentions rather than malice and real strategies rather than manipulative ones.). (p. 452)

Inherently, trusting another includes the assumption that the trust will not be abused (Hosmer, 1995; Whitener et al., 1998). Thus, for trust to develop, the trustee must refrain from engaging in opportunistic behavior, putting the trustor in a vulnerable position as a result of the trustee's action. This necessitates the establishment of a robust normative framework. To put it another way, trust requires the trustor to believe that the trustee wants to keep the relationship going in the future (Hardin, 2002; Lindenberg, 2000), otherwise there is no investment at risk. And, because each human is both a trustor and a trustee in interpersonal trust-building, both individuals require a stable normative frame to guide their activities. This becomes more evident in the technology platform ecosystem, such as social networking.

It has been found that social networking trust "reduces perceived risk and uncertainty" (Hong & Cha, 2013, p. 928). In a social network, trust creates an environment that discourages unprincipled behavior and provides members to connect freely (Shin, 2013). Furthermore, trust enhances information flow and knowledge integration and is thus regarded as a catalytic process for assessing sources and evaluating social capital (Chu & Kim, 2011).

For this study, the focus will be on interpersonal trust as it relates to a recommendation from a qualified informal acquittance in the form of an outside business reference. Given that interpersonal interaction is a dyadic (Schoorman et al., 2007; Jones and Shah, 2016), or one that depends on trust of both parties, it should be analyzed from two different approaches. This interaction can be done in a presence form (face-to-face) or via technology through media applications such as social media.

The proclivity to trust research shows that it is positively correlated to trust, especially in sales relationships (Nicholson et al., 2001). Trust is foundational to social capital (Son and Feng, 2019) and potential social support (Shin, 2013). For example, societies with sophisticated levels of social capital are more apt to promote people who are more willing to be trusting of each another and receive social support those in their social capital network have a greater trust of others (Ikeda, 2013).

Trust in AI

"Treasure your relationships, not your possessions." - Anthony J D'Angelo

Well, that may not be an accurate quote in the future, as an AI driven IPA may help you treasure your relationships, and as a result, you may want to treasure your possession of an IPA. The key to developing human-AI collaboration is to build trust. Forming people's trust in an IPA can help to create true human-machine partnership (Siau & Wang, 2018) and improve human capabilities for a more efficient life and work (Siau & Wang, 2018; Shneiderman, 2020). However, the conceivable risk necessitates the use of a reliable IPA. Although AI technologies, such as IPA, have been used in daily life, individuals still have reservations about trusting them (Gillath et al., 2021; Paay et al., 2020).

Theoretical research extended areas of interpersonal trust to trust in technology. McKnight et al. (2011) offered a comparison between trust in technology to the construct of trust in individuals. The authors built a framework of how trust works in human-technology interactions and proposed “trust functions on three levels: a general inclination to trust technology, a more focused trust in a particular context/class of technologies, and trust in individual technologies" (McKnight et al. 2011, p. 35). These distinct trust levels cooperate and ultimately impact a user's intention to explore technology and utilize a wider variety of features.

In technology, "trust has been identified as a key driver for adoption" (Gefen et al., 2003, p. 707), due to its connection to ambiguity and probability of vulnerability (e.g., Doney and Cannon, 1997; Gambetta, 2000). Most of the research into how users trust technology is grounded in HCI. (Hassanein & Head, 2007). Their research has uncovered the circumstances that influence trust in technology's functional (Lu et al., 2016), hedonic (Hwang & Kim, 2007), and social qualities (Ye et al., 2019). It has been discovered that individuals' trust-building is harmed by perceived privacy problems (Chang et al., 2017). This is especially true in human-intelligent personal assistant interactions, since users are often unaware of the privacy consequences of using them (McLean & Osei-Frimpong, 2019). Research has identified that a crucial feature associated with the acceptance of an AI bot is trust (Wirtz et al., 2018) and contends that anthropomorphism is a strong motivator for users' intention to trust and employ them (van Pinxteren et al., 2019).

The effectiveness of human-AI collaboration depends not only on the precision of the underlying mathematical procedure but also on human aspects, such as trust. People frequently avoid transacting with AI bots due to ambiguity about the vendor's intention or the liability of having their personal information appropriated by hackers (Adamopoulou & Moussiades, 2020). Trust is critical in assisting people in overcoming risk and insecurity concerns. People gain confidence when they feel secure revealing personal information, generating purchases, and executing on an AI bot's suggestion—all of which are necessary for the widespread adoption of e-commerce (Kesharwani & Singh Bisht, 2012). Kesharwani and Bisht (2012) also found that users' trust can influence their adoption-related actions, with trust formed by their inherent perceptions (e.g., perceived risks) of online banking in India. Prior research on e-commerce trust has relied on a variety of inconsistent, insufficient, and variable definitions of trust, making it impossible to evaluate findings amongst studies (McKnight & Choudhury, 2002). Research and actual ecommerce data show that trust is critical to the success of a site and for consumers to purchase (Lowry et al., 2008). As a result, both academics and practitioners require trust as an integral part of the branding of the site.

Trust in AI can be influenced by various human factors, including prior experiences, user awareness, prejudices from personal and societal norms, and perceptions of automation and how it might impact the labor pool. Other factors for the trust of an AI system may include the attributes of the AI system, such as controllability, transparency, model complexity, and associated hazards. Additionally, it is critical to remember that enhancing user trust does not always result in the optimal conclusions from a human-AI partnership. When a user's confidence is at its highest level, the user accepts or trusts the AI system's recommendations and outcomes almost implicitly (Logg et al., 2019). While AI can beat human decision-making in some areas by combining input from numerous sources (e.g. deepmind.com/), having a higher degree of trust could incur higher risks. For instance, an AI enabled navigation system may lead the driver into a safe area with no repercussions on the system. Trust becomes optimal when both parties have something at risk (Wicks et al., 1999). AI's threat would be lacking something at stake, whereas humans are conscious about interrelations and ongoing relationships. Trust is a well-established predictor of embracement of technology (van Pinxteren et al., 2019; Wirtz et al., 2018), and it possesses the ability to mitigate perceived risk by facilitating a user's intentions (Gefen & Straub, 2004).

As AI evolves and learns, it's positioning as a confidant will be relevant to society's use and trust. This is harmonious with the conclusions of Lewandowsky et al. (2000), who described that "individuals trust machines more than humans, even more so when they cannot rely on their judgment" (p. 295). Additionally, Logg et al. (2019) found that people "undervalue the advice of others and place a higher premium on algorithmic guidance" (p. 91). The future dependency of humans on AI will leave little doubt that AI will dominate domains such as interpersonal interactions once trust is established.

Alternatively, institutional trust or trust in institutions is essential in a functioning society to assure the effective operations of the law and order. It also extends to how we trust institutions and their products. Institutional trust is defined as "the sense of security one has in a situation as a result of promises, safety nets, or other institutions" (McKnight et al., 1998, p. 473). It is composed of two constructs: structural assurance and situation normality. Structural guarantee is often referred to as institution-based trust (Pavlou & Gefen, 2004) since the technology is being provided by an organization. Its identities the belief in the process and, in this case, the developers of the algorithm. The term "situational normalcy" refers to an individual's belief that they will succeed due to the fact that the situation is not unusual (Ratnasingam & Pavlou, 2003). For instance, a driver trusts Google maps will provide efficient directions, based on a design that Google maps has historically been offering.

To adopt technology, one must have trust (Madhavan & Wiegmann, 2007; Parasuraman & Wickens, 2008). Research has shown that in order for technology to be adopted, users must have a high degree of trust (Ghazizadeh et al., 2012, Pavlou, 2003). Trust in technology is built when a device may assist users in achieving their goals (Lee & See, 2004). Placing faith in technology has the potential to affect a user's trust on a more intimate level, like interpersonal trust (Muir, 1987). Interpersonal trust is a feature of human–IPA connections as well. In contrast, consumers who do not tend to trust in general are less likely to trust technology and use it to its full potential (McKnight et al., 1998). The concept of proclivity to trust technology envelops trust in general technology and a trusting attitude toward available technology. McKnight and colleagues broke this down into two distinct approaches with a confidence in general technology referring to one’s general beliefs about technology and the other a trusting approach towards generic technology which considers the individual's opinion that technology results in a beneficial outcome (McKnight et al., 1998). For instance, based on a user’s experience and trust with Google maps, they may infer that Apple maps should be equally trusted, but the results may find that the algorithms are superior in the Googlemaps application (Van Alstyne et al., 2016).

Trust in algorithms is contingent upon the tasks' characteristics. Adoption is usually reflected by familiarity with the algorithm (e.g. Google Maps) combined with the magnitude of the risk. While a consumer may trust the algorithm for driving instructions, letting the car drive itself with the instructions, elevates the adoption to another level. Prior use and familiarity provide consumers with confidence for which they can rely on the algorithm for example, Netflix's algorithm-based movie recommendations system is beneficial for the end-user and has been recognized as one of the top features of Netflix (Hallinan & Striphas, 2016). Additionally, consumers rely on algorithms to obtain directions via smartphones. LinkedIn has been using AI to offer suggestions of potential contacts based largely on similar circles and connections they have which you may also recognize. LinkedIn is expanding its use of AI to create more personalization for job opportunities and potentially for applicants to refine more intrinsic traits to narrow the focus on employers and potential applicants (Riebe et al., 2021). "It may be perfectly reasonable to trust the advice of close friends rather than a 'black box' algorithm when making a decision reflecting one's taste" (Yeomans et al., 2019, p. 55). When compared to human decision-makers, AI may appear incomprehensible, creating caution for the user and their intention to trust the AI's suggestions (Yeomans et al., 2019). Research has shown that people tend to be less forgiving of an AI platform compared to humans (Dietvorst et al., 2015). Despite knowing that an AI platform can make a mistake even when advised that the AI's overall capability is superior to that of a human decision-maker if the AI is deemed inaccurate often enough it would result in algorithmic aversion (Dietvorst et al., 2015).

The situation is essential as well. It is judicious to examine the sort of human decision-maker employed as a reference; artificial intelligence may be more trustworthy. Alternatively, research has demonstrated “inconsistencies in how AI is appraised for objective or subjective judgments” (Logg, 2017, p. 92).

Previous research indicates that the “default option is to rely on humans, even when doing so results in demonstrably worse outcomes” (Longoni et al., 2019, p. 448). While humans and AI share certain characteristics such as logic and rationality, AI lacks human-like affective and emotional characteristics as well as intuition. As a result, “people frequently anticipate that algorithms will be less effective at tasks that need human intuition or emotion” (Logg et al., 2019, p. 96), although this may be changing with algorithm appreciation. Prior research denotes a prevalent belief that an "expert system is more impartial and rational than a human consultant" (Dijkstra et al., 1998, p. 5). This predisposition—which is commonly based on the belief that statistical models outpace human intelligence (Dawes et al., 1989)—gives rise to the theory of algorithmic appreciation, which reveals that “people prefer algorithmic conclusions or recommendations over human recommendations in several instances” (Logg et al., 2019, p. 97).

Current research shows that AI is less likely, although not entirely free of, to discriminate based on personal biases (Noseworthy et al., 2020), and prior research on technology adoption has focused on how customers embrace technology-enabled services or commodities based on their perceived utility and simplicity of use. (Chen et al., 2007). Match.com uses an AI-driven algorithm to search a large database of potential suitors. In profiling a prospective match, the AI accesses the personality profiles/tests, and user preferences to produce a suggested list of matches with probabilities. AI's primary strength is scrutinizing sizeable volumes of data and uncovering patterns contained by the data (Davenport & Ronanki, 2018; Zhuo et al., 2019).

However, AI has historically suffered from a fatal flaw of built-in biases due to the original algorithms being created by humans (Ntoutsi et al., 2020). Many researchers have offered approaches to target bias in AI systems, however, the problem may exist at a deeper level, within the actual data used to train the system (Louppe et al., 2017, Madras et al., 2018). For instance, Google recently performed research to establish whether or not the corporation is underpaying women. The results discovered that men were paid less than women for the same profession (Wakabayashi, 2019).

Abusitta et al. (2019) built a new model for alleviating predispositions in AI systems, without reducing their accuracy to tackle the above-mentioned deficiencies. The framework is based on conditional Generative Adversarial Networks (cGANs) (Mirza & Osindero, 2014), which are specialized versions of Generative Adversarial Networks (GANs) (Goodfellow et al., 2014), and they have exhibited extraordinary attainment in generating high-quality, new artificial data with distinct properties. Despite the introduction of eGANs to minimize the impact of biases, there is still work to be done to determine what qualifies as a bias.

Lastly, individuals are typically thought of as rational, but their rationality is limited, not just because they have too little information, but also because they are unable to employ all the information available to them. The result of this is what Simon (1956) called satisficing. Satisficing is a "cognitive heuristic that entails searching through the available alternatives until an acceptability threshold is met" (Simon, 1956, p. 493). Satisficing can be used to explain the behavior of decision makers when an optimal solution cannot be determined, based on the timeliness of the information available.

This means that, in general, in any circumstance requiring action, people are only rational enough to pursue a select amount of information that is attainable (Lewin, 1936). A useful route is to seek counsel from multiple human sources to scale this access; however, all these sources come with bias and potentially self-directed agendas. Alternatively, AI has minimal boundary limits to access data and can process large amount of data that can be in reached in a wide-ranging ecosystem from multiple geographies and domains. Despite the current stigma that AI is focused on selling and marketing, the interactions and relationships that IPAs are developing are quickly changing the trust and dependence humans have in AI. This study supports the idea that trust is a social connection with consequences and that individuals and AI will have equal capability in the recommendation of a qualified connection that will result in some degree of a given trust of a person or AI from the onset.

Trust in an AI platform is gaining momentum (Logg et al., 2019), while still inherently flawed with biases that are the direct result of the creators of the biases (humans) and the data that is used to train the AI (Ntoutsi et al., 2020). Alternatively, humans are flawed due to cognitive heuristics that influence our decision making (Kahneman, 2011, Simon, 1956). While humans still favor human decision makers despite this flaw (Promberger & Baron, 2006), there is a growing confidence in AI platforms based on the equity built on institutional trust. Google is widely trusted (Burguet, 2015), despite the enormous amount of personal data they collect. This trust carries throughout their product line, including their non-anthropomorphic AI platforms (Leviathan et al., 2018). This increased trust in AI may offer significant benefits.

Outcomes of an Effective AI Recommendation

The efficient use of AI can generate numerous advantages. These advantages may be fulfilled in the shape of a product manager insights for designing AI that can enhance interaction with humans (Anderson et al., 2018). For example, an IPA may offer guidance on social capital interactions that include reciprocity and bond strengthening in order to achieve broader opportunities. Organizations that offer social networking (LinkedIn, Facebook, and others) could leverage the AI to drive a valued investment back to the user in the form of social capital connections, which could ultimately provide additional opportunities.

The integration of technology into our daily routines has promoted treating computers like a social entity when engaging with technology (Nass & Brave, 2005; Nass & Moon, 2000). For example, humans frequently thank Alexa for tasks completed (Lopatovska & Williams, 2018). Parents are teaching their children to say thank you to Alexa with the intent of instilling courteous behavior (Beneteau et al., 2020). This is more evident as the technology has remarkable anthropomorphic features (Li, 2015). Due to its human-like (anthropomorphic) features, such personal proximity to technology extends beyond the constraints of social influence and subjective norms. Research (Nass & Brave, 2005; Nass & Moon, 2000) demonstrates that people have social expectations around technology. Humans use the same social criteria to evaluate and responding to the performance of computers as they do to the performance of human individuals, despite the fact that they are fully aware they are talking with machines (Li, 2015). This is not a new phenomenon, we sometimes refer to our cars with a personal pronoun, but it is escalated given that the AI can now respond in anthropomorphic terms.

To date, studies on interpersonal trust with AI are focused on AI-driven IPAs, such as Alexa, Siri, or Google Assistant (Chen & Park, 2021; Hengstler et al., 2016;), while other studies of trust in AI are focused on institutional trust (Logg et al., 2019; Longoni et al., 2019). Interaction with an IPA is analogous to speaking with a person and can lead to an increased cognitive connection over a non-anthropomorphic AI (Kim et al., 2020). Research has explored trust as a conversational agent (Clark et al., 2019), smart home devices (Cannizzaro et al., 2020) and voice-enabled navigation assistants in cars (Pitardi & Marriott, 2021).

Because AI could employ natural language, be able to engage with users concurrently, and have anthropomorphic qualities (such as voice), encounters with them are likely to generate a substance of social presence and build a stronger trust tie

(Chattaraman et al., 2019; Chérif & Lemoine, 2019). Short et al. (1976) defined social presence as "the extent to which technology makes customers feel the presence of another social entity” (p. 24). Ghazizadeh et al. (2012) and McLean et al. (2020) have identified trust as a significant factor in human-machine interactions. Conventionally, trust in technology has been measured by its reliability (McKnight et al., 2009); however, more recent research has focused on its dependability, which is strengthened by having trust in their interactions (Ghazizadeh et al., 2012; Hengstler et al., 2016). Mayer et al. (1995) defined trust as a multidimensional construct that reflects perceptions of another entity's competence, honesty, and compassion. In the field of human-computer interactions, trust has been extensively studied (Gefen & Straub, 2003, 2004; Lee & Nass, 2010; Wang & Emurian, 2005; Ye et al., 2019), and research consistently shows that trust plays a crucial role in persuading consumers' intentions and opinions (Corritore et al., 2003; Cyr et al., 2007).

The advancement of AI across industries has a significant impact on the social-economic domain (Acemoglu and Restrepo, 2017). From an academic evaluation, Huang and Rust (2018) depicted AI as the “primary source of innovation that will gradually replace human jobs in the future” (p. 156). Their research suggested that AI intelligence would evolve from mechanical intelligence (e.g., science, technology, engineering, math, or STEM) jobs), then to analytical capability (e.g., Robo-advisors), and eventually empathy and intuition capacity. This is why significant investments and innovations are happening in the field involving service-driven AI (Singh et al., 2017; Han and Yang, 2018), with noteworthy concentration to those technologies that directly intermingle with customers in the form of intelligent personal assistants (IPA), such as Alexa or Siri (Van Doorn et al., 2017). For instance, Singh et al. (2017) affirmed that intelligent interfaces profoundly disrupt customer interaction with organizations through automated service and sales-driven AI bots in online stores, and the insurance industry has reorganized their sales labor force with the advent of AI (Riikkinen et al., 2018).

In the next decade, anxiety will escalate between how these technologies support and enable our lives while also disrupting them, as they swap typical human practices (such as shopping, driving a car, or even interacting with other humans) hypothetically leading to individuals' alienation. However, there are still unexplored areas where humans are grasping the competency of AI. Recent research (Longoni et al., 2019) discloses that people are tentative to engage in AI-driven medical advice platforms that offer health care, even when they are advised it performs better than human doctors since they consider their medical demands are distinctive and cannot be entirely conducted by AI-driven algorithms. Underscoring the significance of the conviction that people believe their situations are inimitable, the more the participants viewed themselves as distinctive and different from others, the more noticeable their opposition to an AI provider.

However, specific tasks, such as detecting a sickness, are far more far-reaching and personal than others. When the risks are elevated, implementing such tasks incorrectly has more acute repercussions than when the risks are marginal, and customers are less ready to trust algorithms. As one example, one’s health is still at the doctrine of a trained health care advisor with growing AI support. As a result, AI has been historically regulated to structural problem solving, though new frontiers could emerge in the context of interpersonal connections. As AI gets smarter and society becomes more comfortable with the complexities of AI and its capabilities, there may be an evolution to where society begins to trust AI over humans. For example, humans can be fallible; Kahneman (2011) has shown that human decision-making can be severely imperfect. Humans rely on heuristics can that generate biased results. So, could the use of AI optimize outcomes?

In the last century, we have seen incredible technical innovations. AI is near the top of this trajectory since there will be little else that will replace it. Instead, AI is evolving from that of capability used to accelerate labor to that of self-sufficient entities proficient in executing compound duties and accomplishing complicated decisions. AI's function is evolving from ancillary assistance to a self-sufficient entity with whom people interact and depend on. In the future, when AI has more in-depth capabilities in human contexts, it will be challenging to distinguish between an AI-driven bot and a person. With the capture of vast amounts of data and advancements in AI capability, access to all our information is increasingly delegated to AI decision making systems. AI processes occur in a range of situations, including communicating (Carlson, 2018; Diakopoulos & Koliska, 2017; Thurman & Schifferes, 2012), marketing profiling based on online activities (Boerman et al., 2017), synchronizing user activity on social media (van Dijck et al., 2018), and automatically discovering spies (Graefe et al., 2018). The capacity to furnish services or content conditional on an “individual's preferences and consumption patterns is personalization” (Liang et al., 2008, p. 279). AI retains a considerable amount of sovereignty when concluding what to propose to a user (e.g., health advice or a newspaper item) given the access to a gargantuan amount of data and algorithmic. If AI did not do this, we would be left to process too much data, and it would become ineffective.

For the purpose of this research, the terms algorithm and AI are used interchangeably to depict AI-based algorithms that independently execute a task to aid human-decision making. We use the IPA as the modality for an AI based system to communicate since this seems to be the most likely channel of human-to-computer interaction in the future (de Barcelos Silva et al., 2020). The computer science literature demonstrates that participants relied more on algorithmic assistance than their own when addressing a logic problem (Stahl & Wright, 2018). At some point, it is anticipated that humans will be relegated to the three fundamental inclinations that appeal to us: 1) eating, 2) procreation, and 3) interaction (Valsiner, 2020). AI, of course cannot help with the first two items, but in assisting with building connections through social capital, it can enhance the interaction paradigm. Given that AI could have access—if the users allow it, and, in some cases, even if the user does not—to an enormous amount of information about oneself, the results would be noteworthy for users to engage with the content and even drive to make it better. From credit agencies to postings on the internet, a person’s profile can be sketched so that it provides insight into values and interests. This could lead an AI system to guide where a person can grow via personal network connections, and the user can offer more insight to make the AI more accurate.

We are interacting more and more with highly specialized AI algorithms, sometimes even unknowingly. AI use cases are evolving from daily life suggestions (e.g., weather conditions, driving instructions, or selecting a song) to more complex interactions such as platforms that provide interactive AI holograms. We use AI as our personal assistants, matchmakers, and financial advisors (for example, Alexa, Match.com, and Robinhood). Our developing dependence on AI assistance is due to two influences: the proliferation of access and the cost by which we can access (Russell, 2017).

As the capability of AI increases, so does our faith in what it can accomplish. We are now using AI on a daily basis through mapping technology (Googlemaps), weather (Accuweather), autonomous vehicles (Tesla), and IPAs (Alexa/Siri) among other examples. While AI is still nascent in what it can offer in the future (Bostrom, 2014), humans, while cautious, are increasing our comfort level and resulting trust in the AI recommendations (Logg et al., 2019). Alternatively, we are becoming more aware of cognitive biases in human decision making (Kahneman, 2011), and we're increasingly aware of some of the impact of being subjected to others' poor decision making. AI has earned a place in replacing these human decisions in very binary black-and-white decisions, such as fraud protection (Dhieb et al., 2020), yet despite small advances in intuitive based decisions (Cetinic, 2022), humans are historically not trusting of AI without some direct human contact (Rossi, 2018). This could be changing, and new frontier areas that require creative and intuitive operational processes could provide the context for humans to trust AI.

Hypothesis Development

Human-computer interaction literature is a common topic within the information systems discipline; as Nguyen (2018) pointed out, the nature of human-AI interaction still needs to be better understood (Nguyen & Sidorova, 2018). While over 85 percent of CEOs believe AI would give their companies a competitive advantage, customer acceptance of AI services has been described as "slow so far" (Ransbotham et al., 2017, p. 3). Although AI has made significant progress since 2017, there are opportunities to explore trust within the personal ecosystem, given the minimal research.

Technology Acceptance Model

Throughout history, several models have been developed to define and connect individuals, systems, and contextual elements that may have an effect on technological uptake. The most influential is the Technology Acceptance Model (TAM) (Davis, 1989). The distinctive attributes of AI technologies require a broader perspective in recognizing the motivations for embracing and using technology. By integrating social capital literature and the TAM, this study addresses the evolution of human trust in AI. Compared to other technology-related theories, TAM is considered the most prudent theory in clarifying technology behavior norms (Venkatesh, 2000). When compared to other adoption models, Matching Person and Technology (MPT) (Scherer, 1986) and the Hedonic-Motivation System Adoption Model (HMSAM)

(Lowry et al., 2013), TAM explains a significant portion of the disparities (Venkatesh & Davis, 2000). TAM scrutinizes the drivers of people’s confidence and attitudes in their behavior with technology. TAM has been used in understanding relationship building as one of the essential characteristics prompting users’ interactions with the most widely used AI IPAs (Han & Yang, 2018).

Moriuchi (2019) investigated the TAM elements and found that human-like quality technology impacts user engagement and loyalty. McLean and Osei-Frimpong (2019) investigated the motives for embracing and using IPAs by combining human-computer interaction (HCI) literature and TAM. TAM has received some criticism for limited explanatory and predictive power (Chuttur, 2009), its application in this framework is more applicable than its successor models, in that it incorporates use through trust. Finally, Ki et al., (2020) examined how individuals and virtual personal assistants form para-friendship (one way) ties. Trust in capability helps to reduce concerns that the AI may not be able to execute. A study showed that “during an emergency, test subjects were prone to following a robot’s instructions — even after the robot had proven itself unreliable” (Robinette, 2015, p. 1).

Few studies have examined the elements that influence users' trust in their interactions with AI-driven IPAs. Most use either social response (Foehr & Germelmann, 2020) or an information system (Nasirian et al., 2017). Despite this, complete knowledge of what fosters interpersonal trust in IPAs has yet to be determined. This research touches on some of the areas of trust related to social relationships and tasks that are more complex than standard AI tasks, such as directions or playing a song. Mayer et al. (1995) found that "trust is a basic yet a fundamentally deep-rooted psychological component of whether we participate in fight or flight behavior" (p. 353). As a result, humans instinctively classify items as friends or enemies regularly; for example, a burning log is hot and painful to handle, therefore, we learn not to touch it. Humans form deep trusting relationships with other humans and interact more profoundly than with inanimate objects. Because AI-driven IPAs were the first types of technology to display such human-like aspects, such as the voice, users have formed early-stage links with them, seeing them as friends rather than enemies, (Schweitzer et al., 2019; van Pinxteren et al., 2019).

Prior academic research on AI recommendations concentrated on the operational facets of the platform. Lewandowsky et al., (2000), and de Visser et al., (2016) conducted a comparison of AI -based and human recommendation services and the acceptance of AI using TAM. While the theory of TAM has been analyzed in the workplace, where adoption often involves inherent dynamics (Luo et al., 2006), this study looks at individuals' intrinsic reasons and, in particular, their trust levels with AI in a typical business situation. The model was chosen as the theoretical framework for this study because it describes how participants trust technology through use.

To explore age-related variances in intention to interact with AI, this study employed the TAM (Davis, 1989). There are a few models from an assortment of fields (sociology, information systems, and psychology) that have been used to support people's intentions to trust new technology; however, the TAM is the most often cited (Davis et al., 1989; Rose & Fogarty, 2006). Since Davis et al. (1989) established the

TAM model, it has been extensively used to classify the elements of technology reception in multiple contexts and in particular has shown that people's acceptance of technology translates to the use of the technology.

The basis for TAM is the theory of reasoned action (TRA) (Fishbein & Ajzen, 1975), which outlines that behavior is originated from a behavioral intention to execute a particular behavior. Over the course of time, a behavioral attribute is resolved by one's attitude and personal norms observing the conduct in question (Fishbein & Ajzen, 1975). TRA specifically notes that intention to act directly influences behavior because people generally act as they intended to (Dishaw & Strong, 1999). TAM expands the causal links of TRA to justify an individual's acceptable behavior and attitude towards technology, technophilia or technophobia. TAM also postulates that there is a strong connection, between the usefulness of the technology and its intention to use. This relationship is well-known in the literature (Taylor & Todd, 1995; Venkatesh & Davis, 2000).

Bagozzi (2007) theorizes that an individual's behavior and attitude towards technology is based on two key variables: perceived ease of use (PEOU) and perceived usefulness (PU). PEOU is critical in the adoption of new technology (Benbasat & Barki, 2007), and with the advent of IPAs, the ease of use is brought down to the lowest denominate of voice interaction. PU is a bit more complex because it is a more cognitive exercise to determine the value. Perceived usefulness is defined as the subjective judgment of the value offered by the new technology.

Davis extended this to the ease of use and connected that technology that if the technology is easier to use and interact with that it could be perceived as more useful (Davis et al., 1989). Perceived ease of use refers to the effort employed to operate a new technology. Perceived ease of use sways intention to use principally through its influence on perceived usefulness (Davis et al., 1989), as opposed to having a direct effect on intention. A study (Gefen & Straub, 2000) propositioned that the comparative significance of perceived ease of use is widely dependent on the mechanics of the task. For instance, they found that perceived ease of use did not directly affect intention to use a website to purchase a product or service while the use of a keyless entry remote transmitters had rapid adoption due to ease of use. Holden & Karsh (2010) found in a meta-analysis on TAM for the healthcare industry that "perceived usefulness was marginal in predicting trust of usefulness of technology" (p. 3).

Technophilia versus Technophobia (Ideological)

Technophilia generally refers to a strong affinity for technology. "Technology affinity is a personal belief in one's ability to successfully perform or learn a task when dealing with a technological device" (McDonald & Siegall, 1992, p. 466). Contemporary technologies, sometimes known as the fourth industrial revelation (4IR) have resulted in psychological ambivalence because they produce both comfort and disasters of equal proportion. Technophilia (attraction to technology) and technophobia (fear of technology) are two psycho-dynamic expressions of this ambivalence (rejection of technology).

Technophilia (from the Greek - techne, "art/ artifact, skill, and understanding" and o - Philos, "love") refers to the excitement engendered by the consumption of technology, particularly new technologies, such as mobile phones and AI-driven platforms such as intelligent personal assistants (IPAs). Technophilia is defined as tasks that entail the usage of advanced technologies. It establishes itself in the ease with which people attune to the societal changes brought on by technological developments (Amichai-Hamburger, 2009). Fear, distaste, or discomfort caused by modern technology and complicated technological instruments is known as technophobia (from the Greek - techne and - Phobos, "fear") (especially computers). Technophobia is characterized as a fear or anxiety triggered by advanced technology's adverse effects. The dread of negative consequences of technological progress on society and the environment and the fear of using modern gadgets such as computers and advanced technology are two components of the definition (Amichai-Hamburger, 2009).

The person attracted to technology, the "technophile," takes the most or all technologies positively, enthusiastically adopting new forms of technology and viewing this as a way to improve one's living conditions and combat social problems (Amichai-Hambrurger, 2009). Technophiles have optimistic views about the impact of AI, and they consider the ways that AI will supplement human workers and create new jobs because AI augments human capabilities (Huang et al., 2019; Zysman & Kenney, 2018). Technophilia would subscribe to a wide array of business benefits of AI, including enhancing safety features, functions, and performance of products (autonomous cars); optimizing internal business operations (shopping bots); freeing up workers to be more creative by automating tasks (stitch fix); optimizing marketing and sales (Ally Bank), and expanding critical thinking areas (Davenport & Ronanki, 2018).

When combined with hedonistic tendencies, technophilia can be intensified. Hedonism pursues pleasure through consumption, a movement known as "experience seeking." People with a hedonistic focus on “here and now” are capable of using changes which take place in their environment to maximize pleasure for their own benefits. Such behavior results from lack of reflection on the past and the future. Such people do not try to interfere with the changes which take place, but they are determined to avoid distress and maximize pleasure (Nosal & Bajcar, 2004). As a result, Hirschman (1984) divided experience seeking into three groups: 1) Cognition seeking, 2) Sensation seeking, and 3) Novelty. Those seeking cognitive experiences want to stimulate or activate their minds. Sensation seekers feel the experience through one or more of the five senses. Lastly, novelty seekers are looking for unique, fresh sources of stimulation. That is, a consumer's perception of a product's, service's, or activity's uniqueness may generate hedonic value. A unique experience obtained through consumption, such as discovering a new restaurant or trekking, may provide multiple hedonic benefits. Hedonic benefits serve as a status symbol in the consumer's reference group and they deliver temporal pleasure, as the status symbol group of Apple fans highlights the connection between technology and hedonism in the Apple ecosystem and has generated a cult-like following (Ho Lee & Jung, 2018).

Attitudes and psychological factors can significantly impact how technologies are embraced. People's connection with technology is unique in that they either hold excessively favorable opinions of it (perfection bias) or highly negative views of it (rejection bias). Wiegmann, Rich, & Zhang (2001) use the term "polarization bias" to describe this phenomenon; people expect technology to be flawless. If it deviates even a little from perfection, the technology is regarded as untrustworthy. Interestingly, that phenomenon does not exist regarding people and their trustworthiness; people are not expected to be perfect and are more likely to be forgiven when they make a mistake. Humans are tolerant of human error but generally unforgiving of technological blunders. Considering the role of technophilia, a technology attitude is defined as "a person's openness, interest in, and proficiency with (new) technologies" (Seebauer & Berger, 2010, p. 1833). They may have a higher tolerance for errors that the AI platform may make and as a result be more amenable to it.

In contrast, there are pessimistic views that AI will replace all human workers and take all jobs (Frey & Osborne, 2017), and in some cases the wages of the labor force (Manyika et al., 2017). To date, AI has shown successful adoption into society and blending well with human work, but the fear of takeover is not a new revelation. The best-known example is the Technophobian movement of the early 19th century (Autor, 2015). Technophobia is initially referred to those "who resist economic progress by opposing new machinery and work practices in an attempt to protect jobs" (Morris, 1983, p. 12). As a result, the Technophobians symbolically damaged machines owned by manufacturers for various reasons, including perceived poorer output quality and ineffective human management of the transition process (Farrow, 2019). Despite the opposition, the industrial revolution cut consumer product prices and increased the number of products available (Linton, 2005). Replacing humans with intelligent machines brought financial advantages to industrialists and employers while causing fear among workers.

Technophobia is a significant problem in Global society since many people carry negative feelings toward new technology and avoid using it despite the big technological advantages in every aspect of life and creating more safe environments (Sultan & Kanwal, 2017). According to the Chapman University survey on American fears, Bader and colleagues (2015) found that technology was the second most rated source of fear in US, right behind natural disasters. These results suggested that people tend to express the highest level of fear for those things they are dependent on but that they do not have any control over, and that is almost a perfect definition of new technology

Today's Technophobians question technology's embrace and are wary of accepting new technologies that have long-term implications for humanity and society (George, 2011). The introduction of AI and total autonomy creates uncertainty and Technophobian behaviors by inducing human aversion (Clarke, 2019). People with Technophobian views and cautionary voices are wary about AI "inherently undermining accountability and stimulating the abandonment of rationality" " (Seebauer & Berger, 2010, p. 1833) show "AI anxiety" referring to the "fear of the stability and the capabilities of AI" (Johnson & Verdicchio, 2017, p. 2267). They also have fears of AI taking over human jobs (Galloway & Swiatek, 2018). Therefore, I hypothesize that technophilia has a positive relationship with AI in accepting a social capital connection.

Hypothesis 1 -Technophilia

H1: Technophiles are more trusting of AI recommendations versus technophobes.

Foundational research looks at socio-cognitive differences amongst individuals based on sequential age. Historically, researchers had contended that aging was supplemented by a decline in intellectual capacity (Wechsler, 1958). This has evolved to a more multi-dimensional approach that shows variation inability. For instance, crystallized intelligence, the learned intelligence acquired over a lifetime, does not dissipate, while fluid intelligence (the ability to think abstractly and reason quickly) can fluctuate or remain constant (Baltes & Lindenberger, 1997). Fluid intelligence can be significant in rapidly adopting or acquiring new skills, for instance, a mobile technology application (Berkowsky et al., 2018). Age has been proven to affect how algorithms are perceived. Research shows that older generations prefer human editors for selecting pertinent news articles over AI (Thurman et al., 2018), and they were less reassuring that algorithmic decisions are free of bias (Smith, 2018).

Numerous technology applications have been designed to assist with the quality of life for the older generation, from heartbeat monitors (Apple iWatch) to intelligent personal assistants (Amazon Alexa) that can have interactive conversations. These applications are available throughout various industries, such as healthcare and transportation, despite this, older Americans are still less likely to accept new and emerging technologies and realize the possible benefits (Berkowsky et al., 2018).

There are numerous frameworks that delineate elements that manipulate technology adoption. An extensively cited model is Davis's (1989) TAM, which suggests that the use of technology is based on an individual's motivation to use the technology, which is primarily based on the features and capabilities of the application (Marangunić & Granić, 2015). Despite the broad depth of technology applications available to an adult population and the potential benefits, older adults consistently adopt technology at lower rates than younger age groups (Anderson & Perrin, 2017; Choi & DiNitto, 2013; Friemel, 2016).

Older Americans are considerably more inclined to consider adopting a technology if they believe it will be of use to them and will have a beneficial impact on their life, according to Berkowsky (2018). In contrast, young adults use technology to explore options in hopes of lessening the fear of missing out (Milyavskaya et al., 2018, p. 3). Their findings confirm and expand on previous research, demonstrating that a technology's perceived value is critical in determining whether an older adult is likely to accept it even before it is used. The phrase "usefulness" was frequently used in the focus groups, and if participants did not see any current benefit, they were less likely to accept.

Older Americans tend to report lower confidence in using technologies than younger age cohorts (Czaja et al., 2006). Lack of faith can be a significant barrier to successful use or even using a technology (Siren & Knudsen, 2017). Berkowsky

(2018) suggests that lack of confidence can be influenced by a known method of crystallized intelligence (or knowledge that comes from prior learning and experience) that older adults may already be familiar with. For instance, an older adult may be adept at reading a roadmap and not using a GPS navigation system, even though it offers significantly enhanced capability. The TAM model highlights the importance of ease of use in adoption/ acceptance and familiarity (Davis et al., 1989). Davis (1989) defines perceived ease of use as the degree to which a potential technology user believes a system will be painless to use.

Given that older adults are less likely to adopt new and emerging technologies compared to younger people, the following hypothesis is outlined:

Hypothesis 2 - Age

H2: Younger participants will be more trusting of AI recommendations versus older participants.

Reciprocal behavior can be categorized as either direct or indirect (Phelps, 2013). To induce cooperation, direct reciprocity includes paying or penalizing other agents. When adopting direct exchange, humans base their actions on the personal experiences of other humans, with Axelrod's (1984) tit-for-tat approach serving as the quintessential example. An individual in gameplay uses the strategy that they will first collaborate, then subsequently imitate an opponent's prior action. If the opponent previously was accommodating, the player is accommodating. If not, the player is not. The tit-for-tat strategy is an example of reciprocal altruism, whereby a behavior of an individual acts in a manner that temporarily reduces its advantage, while increasing another individual ‘s advantage, with the expectation that the other organism will act in a similar manner at a later time.

Gouldner’s (1960) research has identified reciprocity as a universal dimension in social relationships. Positivity reciprocity suggests that one should repay help with help and negative reciprocity with harm or at the very least not repay them. Gouldner suggests that the norm of reciprocity starts with new social relationship because people are willing to help others knowing that in the future that help will be returned.

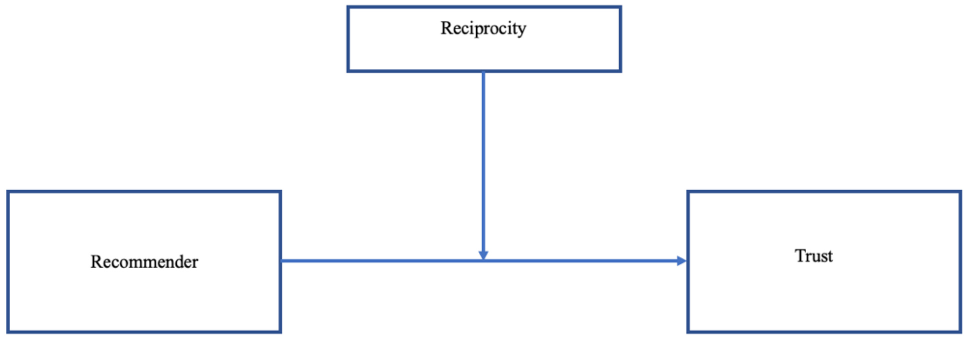
Looking at the need for a reciprocal relationship is important and is the fabric of social capital and the success of societies as well as individual success, but with the advent of advanced technology like AI and the ability to focus on oneself and not worry about returning a favor, reciprocity maybe in jeopardy. Reciprocity gives the impression that the relationship is realistic, allowing intimacy and emotional attachment to grow more easily (Mark & Becker, 1999). In this study, I manipulate the recommendation through reciprocity to see how it affects the development of a relationship with a recommender. When receiving an introduction from someone, there is implied reciprocity of owing the person that made the introduction. Does removing this reciprocity make the recipient more likely to accept an introduction? If reciprocity is present, then I predict that the human source will have a decrease in trust, where AI will show no difference.

Hypothesis 3 - Reciprocity

H3: For human recommenders, the presence of reciprocity will decrease the level of trust.

Figure 2.4.

Reciprocity will Moderate Trust



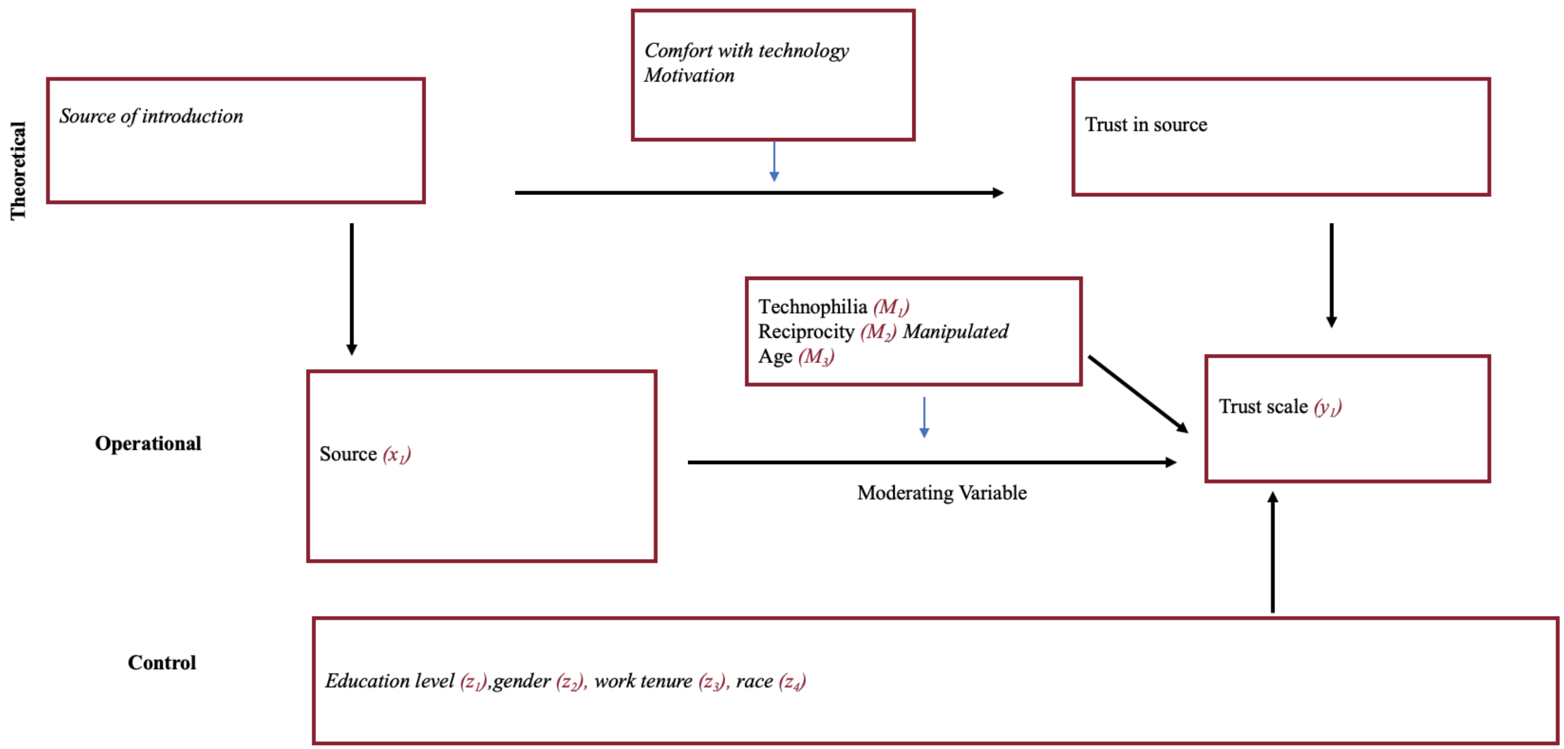
CHAPTER III: METHODOLOGY

Procedures

This study used an experimental design. Specifically, the study is a 2 (source of recommendation) by 2 (presence of reciprocity) between-subjects design. Vignettes were used to manipulate these two conditions. The additional moderating variables of age and technophilia / technophobia were also measured (see figure 3.1). The dependent variable was measured using trust in the source of the recommendation and a trust score to add reliability.

Figure 3.1

Theoretical and Operational Design



Vignettes are at the core of this design. Research finds that vignettes are a viable way to capture survey information and provide "a short, carefully constructed description of a person, object, or situation, representing a systematic combination of characteristics" (Atzmuller et al., 2010, p. 128). We adopted the experiential vignette methodology (EVM) by Aguinis (2014). EVM is broken into two main types: those measuring explicit (i.e., studies, paper, people) and those assessing implicit (e.g., policy capturing and conjoint analysis) processes and outcomes. EVM is ideally setup for this experiment in that it consists of presenting participants with carefully constructed and realistic scenarios to assess dependent variables, including intentions, attitudes, and behaviors, thereby enhancing experimental realism and also allowing manipulations. As discussed later in this section, a pilot study was used to guide the creation of the vignettes to be used. See Appendix A for the text for all four vignettes.

Pilot

As this study is taking a novel approach to manipulating a recommendation source, a pilot study was completed to help guide the creation of four vignettes. The goal was to gauge the impact of the manipulation with different languages being used across a series of potential vignettes. The goal was to see whether a long or short description of the recommender was a more successful manipulation. A mixed-methods approach was used, combining quantitative survey questions (open-ended text entries) with qualitative data from likely style questions. The online pilot survey was designed and published using the survey software Qualtrics (www.qualtrics.com) and was posted in early 2022 through the Amazon mturk (www.mturk.com) platform. The final participant count was

67 (8 respondents were removed due to not completing the survey or offering no qualitative answers). The breakdown was 39 males and 25 females, with an overall mean age of 39 years old. The results showed support for a longer-style vignette with more contextual information about the human and AI actors and that change was incorporated into the final vignettes.

For the key questions regarding selecting between a human recommender or an AI recommender for sourcing an open position candidate, the participants selected the human recommender (60% versus 40%) with a shorter vignette. When more context was provided through a longer vignette, participants switched to the AI sourced candidate (79% versus 21%). See Appendix B for subjective qualitative comments.

Sample

The online survey was designed and published using the survey software Qualtrics (www.qualtrics.com) and was posted in mid 2022. The survey had the capability to be filled out through a computer or mobile device.

Snowball sampling was employed to disseminate the link of the survey; first, it was distributed to the researchers' contacts and was subsequently shared by others on social media or via direct mail (Christodoulides et al., 2012). Recipients were encouraged to forward the link until the researcher determined that the target sample of 120 was achieved. Qualtrics collected the data and presented the vignettes randomly along with survey questions that included scales and control variables. To prevent "participation spamming," no mention of preference towards reciprocity was made during the survey or processing of the data.

Variable Measurement

The scales for both the trust and the technophilia variables were based on the foundational writings from Wang & Benbasat (2005); Dinev & Hart (2006); Morgan & Hunt (1994); and Moorman et al., (1992) and only needed minor adaptations from the originals. The adaptations reflect the AI versus context (Gefen et al., 2003; Lee & Turban, 2001). For technophobia and technophilia, the scale questions were adapted from Martínez-Córcoles (2017), which are based on the Attitudes Toward Computers Scale (Rosen et al., 1987) (see Appendix C for scales and instruments). For the age variable, respondents will enter their age.

Control Variables

This study controlled for gender, race/ethnicity, level of education, and work tenure. Tenure here is defined as the length of employment in terms of years. These variables are frequently addressed in various areas of social dilemma research. Gender differences have an impact on how people define their ingroups and feel interdependent with others (Maddux & Brewer, 2005). Women value relationships and interpersonal ties more than men, while men value depersonalized group memberships and the importance of group identity more than women (Maddux & Brewer, 2005).

Measures

Vignettes are at the core of this design and were rotated through the participant set in order to obtain equal responses per vignette (See figure 3.2). Research finds that vignettes are a viable way to capture survey information and provide “a short, carefully constructed description of a person, object, or situation, representing a systematic combination of characteristics” (Atzmuller et al., 2010, p. 128). We adopted the experiential vignette methodology (EVM) by Aguinis (2014). EVM was an ideal setup for this experiment, in that it consists of presenting participants with carefully constructed and realistic scenarios (See Appendix A) to assess dependent variables, including intentions, attitudes, and behaviors, thereby enhancing experimental realism and also allowing manipulations. As discussed earlier in this section, a pilot study was used to guide the creation of the vignettes that were used.

Figure 3.2

Vignette Design

Randomly Assigned	Source of Recommendation	Presence of Reciprocity	
Group 1	Human	No	
Group 2	Human	Yes	Level of Trust in Recommendation
Group 3	AI	No	
Group 4	AI	Yes	

CHAPTER IV: ANALYSIS AND RESULTS

Analysis and Findings

The results of the snowball sampling (Christodoulides et al., 2012) produced 151 total responses. Several responses were removed due to failure to consent (2), incomplete surveys (2), or flow checks internal to Qualtrics (7). The initial sample (N = 151) was narrowed down to 140 qualified responses based on failure to consent, attention checks, and missing responses.

Manipulation Checks

To ensure successful manipulation of the vignettes, participants were asked to indicate the source of the recommendation, and when reciprocity was present, the value of the reciprocity. Four participants (2.6%) provided an incorrect answer. About 51 percent (39 percent) of the participants were female (male). Overall, participants had about 20 years of work experience and indicated an average age of about 44 years.

Means, standard deviations, minimum and maximum values, and skew were calculated for each scale variable. Frequencies and percentages were calculated for each nominal variable. The treatments were near evenly split between treatments. 34 participants saw Vignette 1, while 35 participants saw Vignette 2. A total of 34 participants saw Vignette three, and finally, 37 participants saw Vignette 4.

As a part of the data cleaning process, the following procedures were taken. All Likert items were converted to a numerical 5-point scale and reversed coded if the question was presented in a negative context (Norman, 2010). Source and reciprocity had two levels. Source could be human or AI, while reciprocity could be present or not present. All other variables were coded into a numerical sequence to provide a more systematic classification process (Field, 2017).

Dependent Variable

Two different evaluations of trust were a part of the experiment. One was based on the trust in technology scale from TAM and was modified and replaced the term technology with AI. A Cronbach's alpha was calculated for this scale, consisting of 6 questions. The Cronbach's alpha (1951) was evaluated using the guidelines suggested by George & Mallery (2018), where > .9 excellent, > .8 good, > .7 acceptable, > .6 questionable, > .5 poor, and ≤ .5 unacceptable. The items for the trust in source scale had a Cronbach's alpha coefficient of .883, indicating good reliability. Alternatively, a single trust question was presented that asked the participant to rate their level of trust of the source (scale 1-10). The trust in source dependent variable displayed consistent results with trust score, which provide a reliability measure to trust. Given the consistency and for simplicity, the trust in source was used as the primary dependent variable for trust. Trust in source, here referred to as trust DV is the main dependent variable.

Control Variables

Control variables showed no material effect, and the results were the same when in the model except for ethnicity. Ethnicity (p =.03) showed a significance, which may be due to the fact that 44% of the respondents self-identified as white Caucasian, and 17% chose not to identify at all. Multi-racial was 12%, and the rest of the categories were low, single-digit percentages. Given the macro level of self-identification and effect sizer of a large population, ethnicity requires more research and could be looked at for further research.

Technophilia Scale

A Cronbach alpha was calculated for the technophilia scale, consisting of 5 questions. The items for the technophilia scale had a Cronbach's alpha coefficient of .864, indicating good reliability. As a result of these reliability scores, the sub-scales were consolidated to form a single value.

Correlations

A Pearson correlation analysis was conducted for the variables using the Cohen's standard to evaluate the strength of the relationships, where coefficients between .10 and .29 represent a small relationship, coefficients between .30 and .49 represent a moderate relationship, and coefficients above .50 indicate a strong relationship (Cohen, 1988). Consistent with the theoretical model, age is negatively associated with technophilia (moderate) and trust score (moderate) and positively associated with education (high) and work tenure (moderate). The results of the correlations were examined using the Holm correction to adjust for multiple comparisons based on an alpha value of .05. Kendall's Tau— "If one variable is continuous and the other is ordinal, then an appropriate measure of association is Kendall's coefficient of rank correlation tau-sub-b" (Khamis, 2008, p. 157) was used to observe the correlation between age (continuous variable) and education level (ordinal variable), with a correlation of r (138) = .38, p < 001, indicating a moderate effect size (Khimas, 2008). This suggests that as age increases, education level tends to increase. A significant positive correlation was observed between age and work tenure, with a correlation of r (138) = .89, p < 001, indicating a large effect size. This suggests that as age increases, work tenure tends to increase. Again, work tenure can only be earned as one gets older. This is consistent with the educational timeline to reach degree levels. Lastly, a significant negative correlation was observed between age and technophilia, with a correlation of -.66, indicating a large effect size (p < .001, 95.00% CI = [-.75, -.56]). This suggests that as age increases, technophilia tends to decrease. TAM has shown this consistency in previous research. No other correlations were significant. These associations were not unexpected and are congruent with the theoretical model.

Hypothesizes Analysis

Hypothesis 1 Analysis - Technophilia

According to Hypothesis 1, an affinity for technology will be a significant factor in the trust of the source for the recommendation. Regression Equation 1 was used in testing Hypothesis 1.

$Trust_i = \beta_0 + \beta_{1i} (Techophilia_i) + \varepsilon_i$

$Trust_i$ = represents the trust in source scale (0-1)

$Techophilia_i$ = represents the level of affinity for technology (0-1)

Table 4.1.
Coefficients - Technophilia

Coefficients [a]

	Coefficient Estimates *(t-statistics)*	p-value
Intercept (β_0)	6.364	<.001*
Technophilia(β_{1i})	5.694	<.001*

* Indicates significance at $p < 0.05$ (one tailed test).
a Dependent Variable: Source_Trust

18.4 % (adjusted R) of variances of trust is explained by technophilia (See Appendix D, 5.2). It can be seen that the p-value is less than 0.001. The null hypothesis can be rejected, which means there is a significant positive relationship between technophilia and trust when the source is AI. From the Model Summary table, the coefficient value is 43.6%, which indicates that 43.6% of the variation of technophilia is explained by the model. To explicitly test Hypothesis 1, I examined the coefficient on the interaction between technophilia and trust of source. As predicted, the coefficient (See Table 4.1) was positive and significant ($t = 5.694$, $p < 0.001$, one-tailed), thereby supporting Hypothesis 1 which suggests that as technophilia increases, so does the trust in AI as a source for the recommendation. Specifically, this can be interpreted that those participants that were favorable toward AI and its advancements will trust AI more than a human. This observation is consistent with the theory underlying this hypothesis.

Hypothesis 2 Analysis - Age

According to Hypothesis 2, younger participants will be more trusting of AI recommendations. Regression Equation 2 was used in testing Hypothesis 2.

$Trust_i = \beta_0 + \beta_{1i}(Age) + \varepsilon_i$

$Trust_i$ = represents the trust in source scale (0-1)

Age_i = represents the age of the participants (21-99)

Table 4.2.
Coefficients - Age

Coefficients [a]

	Coefficient Estimates *(t-statistics)*	p-value
Intercept (β_0)	.983	<.001*
Age (β_{1i})	-.006	<.001*

*Indicates significance at $p < 0.05$ (one tailed test).
a Dependent Variable: Source_Trust

From the Model Summary table (see Appendix D, 5.3), R-squared value is 40.9%, which indicates that 40.9% of the variation of age is explained by the model. 16.7 % (adjusted R) of variances of trust is explained by age. It can be seen that the p-value is less than 0.001. The null hypothesis can be rejected, which means there is a significant negative relationship between age and trust when the source is AI. The coefficient (-.006) is negative and significant (<.001) which suggests that as age increases, the trust in AI as a source for the recommendation decreases (See Table 4.2). Specifically, this can be interpreted that those participants that were older tended to not trust AI and its advancements. The prediction is supported.

Hypothesis 3 Analysis - Reciprocity

For hypothesis 3, an ANOVA model was used to evaluate the interaction effect of source & reciprocity. The interaction between source and reciprocity was included in the model, which showed (see Table 4.3) a statistically significant (<.001) interaction was present (173.279). The adjusted R Square (.721) shows a good model fit.

Table 4.3.
Tests of Between-Subjects Effects

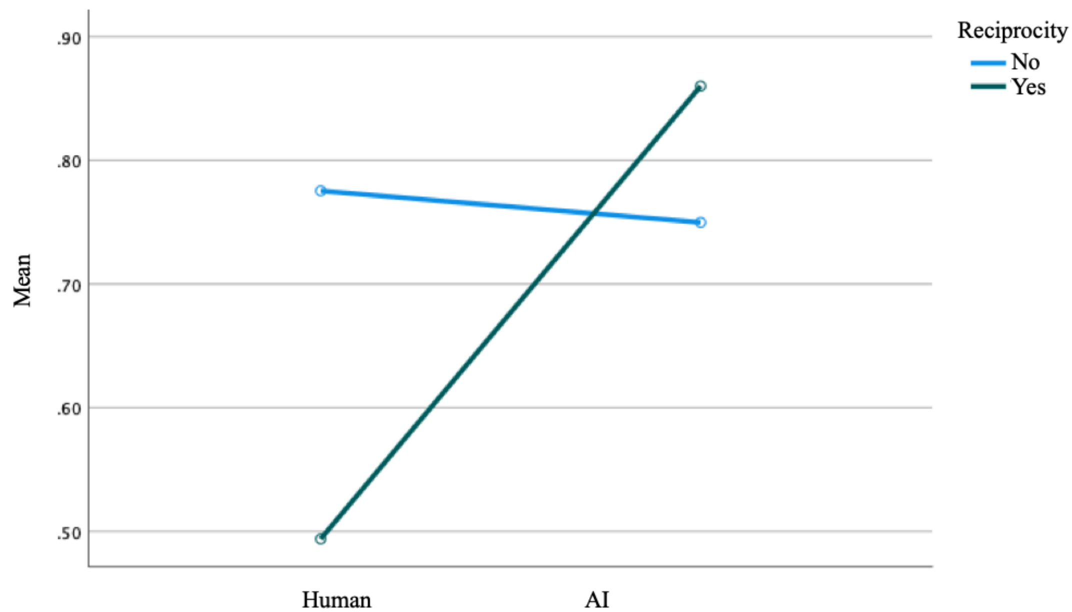
Dependent Variable: Source_Trust

Source	Type III Sum of Squares	Df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	3.224 [a]	3	1.075	120.581	<.001	.727
Intercept	75.761	1	75.761	8500.319	<.001	.984
Source	1.442	1	1.442	161.836	<.001	.543
Reciprocity	.178	1	.178	19.992	<.001	.128
Source * Reciprocity	1.544	1	1.544	173.279	<.001	.560
Error	1.212	136	.009			
Total	80.686	140				
Corrected Total	4.436	139				

a. R Squared = .727 (Adjusted R Squared = .721

The results of the interactions were significant (See table 4.3), indicating significant differences between the levels of both of the factors of source and reciprocity. The interaction effect between source and reciprocity was significant, F (1, 139) = 173.279 $p < .001$, indicating there were significant differences for trust for each factor level combination of source and reciprocity.

Figure 4.1.
ANOVA Interaction ModelF



From the model and research, it can be concluded that reciprocity plays a significant role in the trust of a source of recommendation (See Figure 3). The trust level was relatively consistent between human and AI as a source of recommendation with a human recommender slightly more trustworthy than an AI recommender. When reciprocity was present in the interaction, a significant result appeared with AI substantially more trusted than a human source. Specifically, the data can be interpreted that the presence of reciprocity has a determining effect on the level of trust of the source. The prediction for H3 was supported.

The results of the data showed that where an affinity for technology, technophilia, was high, participants were more trusting of technology, AI, source for a recommendation. Age also showed an effect on trust of a source for the recommendation. Lastly, when reciprocity was present, the trust level for a human source dropped significantly, while the trust level for AI increased.

CHAPTER V: DISCUSSION

The concept of social capital has broadened its impact from social sciences, into the physical sciences, and virtually every area of academic investigation. It has been a focus outside of academia, in business, politics, and community development. Given the maturity of technology, the simplest route to building capacity is to leverage business social networks (e.g. LinkedIn) and make inquiries that prompt recommendations. This is evident when someone receives an unsolicited request to connect and the cognitive process, reciprocity, one follows when deciding to connect. Is the intention good? What will I have to do for them? Should I associate my name with their relationship ecosystem? The source of the recommendation is evaluated as to level of trust and reciprocity.

This study attempted to answer the following questions: 1) are people that are favorable toward technology more likely to trust an AI platform over a human? 2) does age factor into the level of trust in AI when receiving a human-related recommendation? And finally, 3) if there is an expectation of something in return for the task performed, will that influence the level of trust of the particular source? This paper addressed these questions by examining the association between AI perception and social capital through the use of information and communications technology (AI) as an intermediary.

This study considers the idea that trust is a relationship construct. This requires a subject as a cognitive agent and a recommender (trustee) as an agent capable of causing some impact on the outcome or its behavior, as well as the causal process and its results. The results suggest that how we frame the vignette with the presence of reciprocity is a key factor for participants deciding how much a reciprocal expectation influenced them, which in turn affects whether the experiment yields an AI trust result or an AI distrust. Reciprocity is the implied contract of mutual benefit between agents (Falk & Fischbacher, 2006). Reciprocity can be between human agents or a human and a non-human entity, such as paying a vendor for electricity. This mutual commitment offers bonding or commitment between agents that can enhance outcomes.

The experiment tested how the agent type (AI vs. human) affected how much participants were influenced in decision-making tasks. Participants were indifferent towards the agent type until reciprocity was added to the vignette, then, regardless of human expertise, participants showed a clear effect of AI trust. The experiment also showed that one key factor behind the malleability of the decision is participants' affinity toward technology. Will the presence of reciprocity influence the decision on using AI as a trusted source for social capital recommendations? The responses suggest that a large majority of participants believed and remembered their type of introduction (i.e., AI or human condition) and if a reciprocal expectation was present. The results showed that the presence of reciprocity was taken into account when evaluating the trust of the source of the recommendation. Its natural, or what we call "human nature," to have prejudices and stereotypes (Amodio et al., 2021). AI is widely believed an expert system, particularly in computational capability (Ragot et al., 2020). We also tend to have a higher "judgement" bias or bar towards humans than AI (Logg et al., 2019), as we tend to be a bit more forgiving of AI, thinking "it's just a machine with no feelings" (Ragot et al., 2020, p. 3). This bar offers an entry opportunity for AI to advance in areas that are creative and empathy-based, in which historically, AI has had minimal capability.

Although we are moving into an era where AI is quickly becoming a complimentary partner, we are still unsure about what AI will bring to society at the relationship level. AI is critical to social progress, and it has yielded revolutionary achievements in boosting labor efficiency, lowering labor expenses, optimizing human resource structure, and creating new work demands (Duan et al., 2019). "AI is a computer system with intelligent capabilities equivalent to human beings to infer, recognize and judge" (Ishizuka et al. 2017, p. 2).

AI is poised to dramatically alter the future of society. During the continuing COVID-19 pandemic crisis, we are seeing a significant shift in the use of AI systems, which has forced many to increase AI-human interactions in order to maintain safe and effective distance. There was growth in using AI-driven cleaning robots in order for employees to focus on stocking shelves and ensuring that customers have the products they require during a crisis (Howard & Borenstein, 2020). The COVID-19 pandemic generated the need for more AI-human interactions to improve safety and achieve organizationally and socially valuable outcomes. For example, AI bots were used for handling packaging to reduce the propagation of infectious bacteria. It also provided opportunities for individuals to interact more with AI through IPAs. The growth of IPAs has driven innovation and comfort with using IPAs. For instance, ordering groceries with Alexa or using Siri for verbal directions. With the interface becoming more palatable and AI's capability in accessing large amounts of data with no implied contract of reciprocity, AI could serve a more trusted human cognitive role, given its lack of expectations.

We live in a society of technology. It is infused with almost every interaction we have today, from driving cars, to internet searches, to banking and shopping. We have either grown to love it, hate it, or fall somewhere in between. Technophilia measures our affinity towards technology and refers to an individual's attraction to and enthusiasm for using advanced technologies (Osiceanu, 2015). According to Anderson (2018):

> In other words, technophilia is a worldview that sees all new technology as inherently positive and beneficial to human life. The language we use to describe technology is indicative that we live in a time of technophilia. Phrases like technological advancements or technological progress are commonplace; we seem to lack the language to describe changes in technology that do not imply that they are inherently beneficial. Additionally, deeming devices with the capacity to connect to the Internet as "smart" (e.g. smartphones, smart televisions), rhetorically reinscribes an ideology of technophilia while granting epistemic credit to inanimate devices. (p. 8)

Technophiles regard technological advancements as natural societal processes, enhancements to daily life, or forces that will improve reality. Technophiles demonstrate a readiness to try new things and be open to change (Martinez-Córcoles et al., 2017). The results showed that participants who had a predication towards technology were more favorable towards the AI platform. Building a capability in providing quality human recommendations will take time and input. The group most likely to drive and support this innovation will be technophiles. “Technophilia fosters the relationship between intents and actual transactions” (Amor & Yahia, 2021, p. 1). Accordingly, technophiles have no fear and enjoy using technology.

The drive to innovate and the proponents to evolve the rapid innovation is good, but it is important to be judicious in our evolution with technology. Our dependence and surrendering to technology may have an impact on social connective bonds and how we perceive ourselves in the world. AI is capable in many domains that require intricate equations and repetition to perform, but it is still lacking in cognitive capability (Natarajan & Gombolay, 2020). We are in the courting phase of the AI revolution and enjoying our newfound love for things that make our life better, but our growing dependency could have broad effects on our capability. “The Internet makes pupils stupid” (Anderson, 2018, p. 9).

Despite the societal importance of networking (social capital) in driving career success, no prior research has investigated how people react to the technological replacement of a human recommender. This study’s results show that while the public tends to prefer introductions by other humans than AI slightly, once an expectation of a return in the form of a reciprocal bond is expected, humans feel threatened by the recommendation. This is because technological (vs. human) recommendation replacement has unique psychological consequences and expectations.

Given the importance of what social capital can provide, both in the giving and the receiving, AI may take a more prominent role in aspects that impact us. Society must embrace, interact with, and integrate their behavior with AI systems in order for AI to be successful with outcomes (Glikson & Woolley, 2020; Lichtenthaler, 2018), and organizations will be early adopters in driving the growth of AI in unprecedented areas. "'Organizations are entering a terrain marked by unprecedented collaboration among managers and intelligent machines,' according to researchers. There are currently no maps available for navigating this difficult and unfamiliar terrain" (Kolbjrnsrud et al., 2017, p. 6).

An obvious first place to start at where AI can be tested in reciprocal scenarios would be social capital-driven networks such as LinkedIn or Facebook, as just a few examples. LinkedIn (parent owner Microsoft) has made substantial use of AI to enhance the customer experience with rapid access to employment recommendations, potential pertinent knowledge postings and suggestions for connections. LinkedIn currently uses a hybrid system, much like Netflix does. It uses a collaborative filtering methodology for providing suggestions based on other people in your network and if they have shown interest. This is combined with tagging of information around the person from role to industry and interests to offer a combined suggestion (Li et al., 2020,). Today, LinkedIn doesn't incorporate any form of reciprocity through a favor bank or the ability to manage those. In the future, LinkedIn could offer AI to manage calculations for introductions and what the return value could be. It could also offer higher quality suggestions that have more of a strong value than just a basic name to add to one's list of contacts. This can be achieved by capturing and assigning more data about each individual user. Today, LinkedIn is limited to the data that the user offers, but if it extended this model to include reciprocal behavior and traits including feedback, it could build a deeper model from which AI could act on and be more beneficial to the user overall. For instance, if a user had a comprehensive data schema of their traits, values, and capabilities including level of competency, and domain approach, whether business acumen or artistic endeavors or others, AI can know leverage this information to provide recommendations to people far outside the typical reach of a LinkedIn user today.

Once this has been established a transitive relationship methodology could be employed to approach unique problems. For instance, in a transitive relationship, the model suggests that if one user (A) trust another user (B) and the other user (B) trusts a third user (C), then it is postulated that user A will trust user C. This would be ideal for direct interactions but also could be useful in an extended transitive relationship for content on the internet. For instance, the model could be extended to user C_{n+1} through multiple layers of transitive relationships. Thus, user A would trust user C_{n+1} based on the extended network. Using AI to manage the reciprocal relationships, an approach that could marginalized internet trolls could be realized if the option to only view comments by relationships in the extended transitive ecosystem. Online gaming platforms have some of the initial foundations to this with the promotion of grouping of players through alliances, guilds, teams etc. These groups tend to self-manage but through capability and reciprocity. An opportunity for gaming platforms is to extend the recognition system and use the back AI system to drive engagement with players and minimize bad game play from insensitive players.

Theoretical Implications

SCT is one of the most important ideas that has been used in social media. While other theories, such as the social gratification theory (Glanville & Paxton, 2015) and the social network theory (Radil & Walther, 2019), have been used to investigate social media, the SCT theory has been found to support the concept of social media more effectively, due to its focus on the involvement of a network of people in the social capital building.

According to self-determination theory, it is likely that there may be a more extrinsic than intrinsic motivation to accept the recommendation of a technology platform. Extrinsic motivation can become autonomous, i.e., experienced as being part of oneself or positioned as a self-promotion symbol of how innovative the respondent may be. For instance, a participant may select the AI recommendation in order to symbolically demonstrate innovative thinking, even if the results are unproven. "Organizational leaders to frontline employees display symbols either as an extension of themselves or to gain favor with symbol observers "(Thomas, 2021, p. 42).

This research may offer an additional element for reciprocity which may be the option to avoid reciprocity altogether. Kindness encompasses both the outcomes as well as the intent of an action. This research summarizes the practical finding that the same outcomes of an encounter are perceived and reciprocated differently, depending on the core intention of the source. In Fehr and Schmidt (1999), and Bolton and Ockenfels (2000), agents strategically position their reciprocal behavior to reduce the imbalance of the mutual contract. Falk & Harrison (1998) explored the strategic positioning in detail of this question using the experiment of the prisoner's dilemma with a subsequent sanctioning stage. Their results showed that reciprocal behavior is principally motivated as a response to benevolence, as opposed to focusing on the imbalance of a mutual contract. If a behavior is exhibited from a negative reciprocal perspective, as opposed to benevolence, it can be denied or avoided altogether. This research presented scenarios with a potential negative element with the results showing a difference in trust level when the negative reciprocity was present. Hopefully, the experimental results will help the theoretical development of social capital and motivate formal social capital models to incorporate the element of reciprocity avoidance.

Additionally, the results could speak to the growing field of AI and the theoretical development in the sociology of technology. The theory involving AI algorithms is robust and as AI continues to innovate with new theory development around AI's capability in non-mechanical such as emotional and interpersonal connections. These results could assist in offering perspectives of elements to include in reviewing how people approach AI relationships. AI's rapid innovation is driving toward all facets of human being intelligence and the last frontier will be the cognitive and societal relations. Alan Turning (1948) said "if a machine behaves as intelligently as a human being than it is as intelligent as a human being." At the birthplace of AI, the Dartmouth conference McCarthy expounded on Turning's comment to include "every aspect of learning or any other feature of intelligence can be so precisely described that a machine can be made to simulate it" (McCarthy et al., 2006, p. 12).

Today's research will benefit from the data presented in this paper because it shows human acceptance of AI as a trusted source in situations that would normally be reserved for human cognitive processes only. It further highlights how AI may have a more prevalent position in situations that involve emotional or reciprocal behaviors. The outcomes of this research could be used to enlighten theoretical models of the circumstances under which unintended reciprocity systems produce domains for various social principles.

It can be used as an evaluation criterion for understanding the repercussions of intended mutual benefit. Users of AI should pay close attention to the services that seem innocuous and may impact their social capital worth in the future. AI could elevate by expanding access and scope of prospects for social capital connections. However, it is important to note that even though AI may be advantageous and useful it might have some significant negative impacts with a lack of future social capital bonds.

Trust is "a psychological state comprising the intention to accept vulnerability based upon positive expectations of the intentions or behavior of another" (Rousseau et al. 1998, p. 395). Reciprocity implies a "pattern of mutually contingent exchange" (Gouldner 1960, p. 161) that attaches to self-directed interests. The study looked at the scenario-driven decision with implications that result in trustworthiness. Cárdenas et al. (2008, p. 47) report that "expected reciprocity is a better predictor of trust than social distance or risk preferences." This research could provide some additional insight into the lack of perceived reciprocity or even negative reciprocity that influences decision outcomes.

Practical Implication

AI may be used to extract behavioral data and lifestyle choices from transactional data, which has ramifications for behavioral interactions. Researchers may, for example, use AI to gain a more detailed understanding of how Norman's (1963) “Big Five” personality traits manifest in our values and aspirations. In this regard, designing experiments to study how colleagues and unknown prospects may modify their conduct to promote or hide their "true" personality and ideals could be quite fascinating.

Users can extract valuable recommendations from a social capital network, which results in users being able to communicate directly with one another (Katz & Shapiro, 1985; Rochet & Tirole, 2003). In light of the "computer in the middle of every transaction" (Varian, 2014, p. 1), these direct interactions between users are increasingly mediated by technology-driven interactive learning processes, based on data collected about each user involved in the exchange connection. LinkedIn, for example, has historically benefited from substantial interaction effects, in which the value that users gain from LinkedIn is predominantly derived from the chances for users to connect directly with one another. This is spread through LinkedIn, which suggests network contacts based on who you already know. The worth of each individual user increases exponentially as the user community grows.

A social capital connection can rely on someone based on dependable habits, but trusting someone necessitates that they act in the trustor's best interests. Trust is a cognitive activity that requires the trustee to maintain the trust and their intent to do so. AI, which is a human-made object, does not have the quality of intent. Instead of trust, a more practical evaluation could be the reliability of AI to provide an accurate recommendation. Consumers of AI should maintain their primary criteria for capability on reliability, as opposed to trusting.

Corporate officers are increasingly aware that AI connected to the growing data cloud is the new oil fueling the economy and should be treated as a strategic asset (McAfee & Brynjolfsson, 2012; Perrons & Jensen, 2015; Varian, 2014). Since this powerful combination will supplant much of “what you know” the complimentary adage of “it’s not what you know, it’s whom you know” is ever more pertinent. If corporate officers can increase their networks through a scalable AI platform that offers rapid and effective introductions and that can build their network, the results will be a corporation with limitless opportunities. The findings may also inspire novel predictions regarding broader societal consequences of technological interactions.

Limitations

The researcher is aware of several limitations of this research. The first limitation is that the research does not focus on the capability of AI, social capital management, or the development of trust. This is because these topics are largely covered in the literature. This dissertation focuses on the human perspective of reciprocity, and it discusses how individual behaviors may influence trusting perspectives shared between people. There are many limitations to consider, but the researcher highlighted a few to consider when reviewing this research.

First is the power of reciprocity and the associated cost. This research used a monetary amount of $100 for the recruiting process. Using third-party recruiting firms cost significantly more than this and although the researcher picks a lower denomination to make the transaction more personal in nature, some consideration should be given to a larger amount, potentially in the tens of thousands of dollars. It would be interesting to see how participants would react to the larger dollar amount given that this may make it more of a corporate decision, using corporate funds, as opposed to a personal decision.

Transparency in how AI-based recommendation services' outputs are presented to potential customers may be required. The “black-box” perception is a major impediment to adoption. Adadi & Berrada (2018) present a variety of ways for explaining AI models, all of which are highly technical and sophisticated; however, Anic & Wallmeier (2020) suggest that in order for a complicated AI platform to be seen as trustworthy, information about it must be "intuitive and easy to comprehend" (p. 2). Behavioral and experimental researchers should look into how AI results and descriptions are presented so that people gain faith in the AI platform and eventually perceive it as useful.

There is the continued possibility of algorithmic data biases (Lambrecht & Tucker, 2019), which can be both positive and negative biases. Positive, as demonstrated by the LinkedIn AI platform, can be extremely beneficial, whereas negative data bias effects and will result in the perceived value of the platform decreasing (Parker et al., 2016). For example, Microsoft's AI-powered chatbot, Tay (a Twitter bot that was meant to learn to engage people through informal and fun social media chats), quickly picked up racist and highly nasty language from Twitter users, dramatically lowering the perceived value. As this example shows, embedding platform AI capabilities in exchange relationships and user networks on multisided platforms carries significant risks (Russell et al., 2015), highlighting the need for future research to take into account both the intended and unintended consequences of AI effects.

Cultural backgrounds could be an interesting construct to investigate, given the unclear results that ethnicity showed in the experiment. Different ethnic groups bring different perspectives from cultures and upbringings; hence, future studies may examine people from diverse clusters of users and may add other variables like skepticism.

The results of the analysis may represent the direct impact of society on AI perception. Those with a higher cognitive social capital maybe have a negative effect toward the use of AI. Although not shown in the paper, when it comes to the preference between AI and humans, those with frequent contact with others may prefer humans over AI. “Those with close contacts with others may have difficulties in adopting a ‘relationship’ with AI.” (Inaba & Togawa, 2021, p. 98). Alternatively, there is evidence to show that those that have difficulties interacting with others may find building a relationship with AI is a lower barrier of entry to building out trusting relationships: “AI can increase communication efficiency and improve interpersonal perceptions” (Hohenstein et al., 2021, p. 2). This result indicates that a positive relationship with technology has a positive impact on participants’ attitudes toward engaging AI in cognitive areas. Thus, the answer to this question can also be considered for further research, as this research shows limitations in understanding how AI is accepted in a cognitive role.

One significant factor in establishing trust between humans and AI is the perceived anthropomorphism of the AI. Anthropomorphism refers to applying human-like qualities to nonhuman things. Prior work has shown that increased anthropomorphism of an AI leads to a more positive interaction experiences, even through voice (Natarajan & Gombolay, 2020). One area to consider is how the voice delivery of the recommendation may impact the results when an explicit reciprocity directive is made.

From a research method perspective, the sample size (n=140) meets minimum criteria to ensure statistically significant results although a larger size sample set would have been more ideal. The participants were captured through a snowball method on email and an opportunity existed to extend the time frame or encourage additional respondents. Additionally, the sample set should include non-internet users. Today, 7% of the adult population in the U.S. do not have use of the internet (Perrin & Atske 2021) and there is an opportunity to include this population in the sample. As a result, the sample maybe biased towards participants who have an affinity towards technology.

Finally, this paper did not directly address the ultimate research question on how AI will affect SC in the future. This is further complicated by the arguments on how to measure social capital and even if it can be measured. In order to improve a state, one needs to know what the current state is. “There is considerable debate and controversy over the possibility, desirability, and practicability of measuring social capital, yet without a measure of the store of social capital, its characteristics and potential remain unknown” (Falk & Harrison, 1998, p. 3).

Conclusion

This research showed that affinity towards technology, technophilia, and the presence of reciprocity, the expectation of a return, were influential in the trust level of a recommendation. This research highlights the perception that a non-human source, AI, is perceived as not having an expectation of a return, even if the reciprocal expectation is in the form of a paid service. Social capital generally arises through spontaneous sociability (Fukuyama, 1995). Therefore, explicit efforts designed to create social capital can be challenging in normal circumstances but especially so during a pandemic, when individuals’ physical relationships and interactions are discouraged to reduce viral transmission. As the pandemic subsides, society’s comfort level with technology has increased, and leveraging different technology platforms can provide enhanced career outcomes if the trust is established.

This research evaluated the connection between the source of trust and reciprocity as a notion within the social sciences. The research demonstrates how incorporating behavioral characteristics into the design and execution of an AI system is a difficult issue. User's trust in AI-based applications and services is an ethical and moral question. The rapid pace of technological advancement, the multiple dimensions of social capital, the uncertainty of where trust is required, the best ways to approach recommendations with different expectations, and the best ways to understand transparency measures are all obstacles to implementing an AI platform that is valued in social capital spaces. The results could directly affect the adoption and success of AI technologies in individuals and in social capital scenarios. This, in turn, could provide insight into the design of a reliable (trusted) AI platform. Lastly, they could provide guidance on the expectation of cognitive trust in AI and explainable AI.

AI is a phenomenon that affects individuals, organizations, and societies as a whole. The ability of algorithms to accomplish complicated tasks and help decision-making supports AI adoption in a variety of sectors. As a result, it is important to talk about the nature and dynamics of trust in the context of human-AI interactions, with a focus on trustworthy AI qualities. AI has established footholds in key areas, such as mapping and automated services, and it is nascent in social-economic domains. This research looked at how social capital may not have a valid normative objective of relative trustworthiness. Measuring AI through the use of the concept of trustworthy AI to signify a moral objective should define trust in AI carefully.

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APPENDICES

Appendix A: Vignettes

Vignette 1 -- Human Source, Low Reciprocity

You are the CEO of a mid-sized company in the mid-west that has had a sudden surge in sales. You are seeking a candidate to fill one of your key logistics roles. Given the urgency and limited time to seek candidates, you sourced a recommendation from a professional contact with significant industry experience. The professional contact works outside your company at a similar business.

Vignette 2 -- Human Source, High Reciprocity

You are the CEO of a mid-sized company in the mid-west that has had a sudden surge in sales. You are seeking a candidate to fill one of your key logistics roles. Given the urgency and limited time to seek candidates, you sourced a recommendation from a professional contact with significant industry experience. The professional contact works outside your company at a similar business.
The professional contact is expecting a monetary gift (tickets or special access) in return for the recommendation.

Vignette 3 -- AI Source, Low Reciprocity

You are the CEO of a mid-sized company in the mid-west that has had a sudden surge in sales. You are seeking a candidate to fill one of your key logistics roles. Given the urgency and limited time to seek candidates, you sourced a recommendation from a trusted AI recruiting platform that has received accolades for accuracy in recommendations.

The AI system has access to an extremely large amount of data on candidate profiles, has received multiple awards for accuracy, and was built by a team of business and technology consultants in order to minimize bias. It is capable of cross referencing your leadership approach and profile in order to provide the best match.

Vignette 4 -- AI Source, High Reciprocity

You are the CEO of a mid-sized company in the mid-west that has had a sudden surge in sales. You are seeking a candidate to fill one of your key logistics roles. Given the urgency and limited time to seek candidates, you sourced a recommendation from a trusted AI recruiting platform that has received accolades for accuracy in recommendations.

The AI system has access to an extremely large amount of data on candidate profiles, has received multiple awards for accuracy and was built by a team of business and technology consultants in order to minimize bias.

It is capable of cross referencing your leadership approach and profile in order to provide the best match. The service requires a fee to access.

Appendix B: Pilot Survey Comments

Some of the subjective comments are shown below that demonstrate that the longer vignette provides more detail for participants to act on:

- “It is a mid-sized company, and I wouldn't feel as much pressure when hiring someone. But I would still rather have the AI make a prediction. I trust AI more than I would trust myself to make a decision. Then also, I wouldn't have any personal regrets if the AI made the choice.” – 44-year-old female
- “In the extended version we learned the AI has been producing good results. I would imagine AI can come in many flavors and would be more trusting of one with a quality track-record.” – 47-year-old male
- “I felt the extended version was more persuasive because it gave more information about the actual qualifications of both the colleague and the AI, and it was more detailed in general. Details tend to persuade me more, as I then feel like I have more pertinent information and can't learn much more than I already know about a situation before making a decision.” – 36-year-old female
- “I think AI generally would do a better job with a large amount of data and it wouldn't skimp over it to make judgments based only on feelings.” – 35-year-old male

Appendix C: Scales

The scales for the trust construct were built based on the foundations from Dinev & Hart (2006); Morgan & Hunt (1994); Moorman et al. (1992); Wang & Benbasat (2005) that was adopted from TAM and only needed minor adaptations from the original ones. These minor adjustments reflect that the adoption process referred to an AI service as well as a comparison alternative, which used a human versus AI (Gefen et al., 2003; Lee & Turban, 2001). Trust showed as a .93 reliability according to the research done by Belanche, et al. (2012), while technophilia showed a 92% in reliability (Martínez-Córcoles, et al., 2017).

Trust in Technology Scale Questions

- I have faith in what the AI is telling me
- The AI provides with me unbiased and accurate social capital recommendations
- The AI is honest
- The AI is trustworthy
- I believe AI wants to know and understand my needs and preferences
- I believe that AI provides a reliable service
- I can trust the information provided by the AI

Trust in Humans Scale Questions

- I have faith in what the human recommender is telling me
- The human recommender provides with me unbiased and accurate social

capital recommendations

- The human recommender is honest
- The human recommender is trustworthy
- I believe human recommender wants to know and understand my needs and preferences
- I believe that human recommender provides reliable guidance
- I can trust the information provided by the human recommender

For technophobia and technophilia, these are the scale questions adapted from Martínez-Córcoles, et al. (2017), which are based on the Attitudes Toward Computers Scale (Rosen et al., 1987), and they show a validity of .92 in a nationwide study, and higher on smaller scale studies.

Technophobia

- I feel an irrational fear of new equipment or technology
- I avoid the use of new equipment and technology
- I feel uncomfortable when I use new equipment or technology

Technophilia

- I am excited for new equipment or technology
- I'm afraid of being left behind if I cannot use the latest equipment or technology
- I enjoy using new equipment or technology

Demographic Scale Questions

- What is your age?
- Indicate gender
- What is your ethnicity/race?
- What is the highest level of education you have completed?
- Have many years have you been in the workforce?

Appendix D: Tables and Figures

Table 5.1

Classification of Variable

Variable	Role	Measure
Participant	Primary key	Nominal
Vignette	Secondary key	Nominal
Source	Independent variable	Nominal
Reciprocity	Independent variable	Nominal
Gender	Control variable	Nominal
Ethnicity	Control variable	Nominal
Industry	Control variable	Nominal
Trust score	Dependent variable	Scale
Source trust	Dependent variable (alternate)	Scale
Technophilia	Independent variable	Scale
Age	Independent variable	Scale
Education level	Control variable	Scale
Tenue	Control variable	Scale

Table 5.2

Regression Model Summary Technophilia

Model Summary [b]

	R	R Square	Adjusted R Square	p-value
Model	.436 [a]	.190	.184	<.001*

a. Predictor: (Constant), Tech
b. Dependent Variable: Source_Trust

Table 5.3

Regression Model Summary Age

Model Summary [b]

	R	R Square	Adjusted R Square	p-value
Model	.409 [a]	.167	.161	<.001*

a. Predictor: (Constant), Age
b. Dependent Variable: Source_Trust