The Role of Information Quality and Quantity on the Performance of Partner-Selection Strategies in B2B Digital Platforms

A thesis submitted for the degree of Doctor of Philosophy

by

Jun Chul Kim

Brunel Business School

Brunel University, London

October 2023

Declaration

I hereby declare that the thesis is based on my original work, except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at Brunel University or other institutions.

Name: Jun Chul Kim

Date: 27 October 2023

Signature:

Dedication

In gratitude to Hajung *for the countless cups of 'Flat White', words of encouragement, and unwavering belief in me.*

For my wonderful kids*, Jeehan and Jeeah, hoping your wisdom comes without the need for a PhD title.*

Abstract

Partner-selection strategy has a significant impact on the network configuration and financial performance of Information Technology Outsourcing (ITO) firms in both traditional marketplaces and digital platforms. Despite a growing body of literature on network theory and relational governance examining the superiority of Dyadic Trust and Reputation, it remains unclear how the buyer-supplier network is altered by two different selection strategies and its impact on the performance.

This study employs a simulation-based approach to develop new theories proposing possible answers to the research questions. Simulation models implemented in this study are based on transaction cost theory and relational exchange theory to examine the impact of partner selection strategies on buyer's long-term performance within the context of B2B digital platforms. The study tracks the evolution of network structure and its effect on long-term cost performance, depending on the partner selection strategy adopted. The simulation results indicate that the quality and quantity of information in the marketplace affect the supply chain structure based on the partner-selection strategy adopted by buyer firms. A partner-selection strategy that utilises a centralised feedback system in B2B digital platforms to enhance the accuracy of supplier reputation is better equipped to handle changes in technological unpredictability and reduce partner opportunism. Additionally, higher quality information in the B2B digital market leads to increased visibility of reliable suppliers.

This study contributes to the field of strategic management by systematically analysing the impact of information quality and quantity on the performance of buyers taking a partner-selection strategy in the context of B2B digital platforms and relationship network theory. The simulation results indicate that information accuracy and transaction volume can lead to the faster and cheaper identification of reliable suppliers in the uncertain environment of ITO transactions. The simulation results suggest that the relative cost advantage of relationship-based strategies may decline in B2B digital platforms where trustworthy suppliers can receive more business opportunities outside of the relationship-based pool. This suggests a premium cost may be required to maintain reliable supplier relationships, adding another boundary condition to the relational network theory. The findings can be used by managers in B2B digital platforms to prioritise investment in attracting new buyer firms that are still hesitant to join the platform.

Table of Contents

List of Tables

List of Figures

Chapter 1 Introduction

Chapter 1 presents an overview of the study, starting with the Research Rationale that explains the research background. After discussing the related literature, the research gap and question are identified. Next, the research approach and methods are described to address the research question. Finally, the chapter concludes by outlining the structure of the thesis.

1.1 Research Rationale

Online outsourcing is a promising alternative to traditional marketplaces and linear supply chains in the IT era (Van Alstyne and Parker, 2016). This type of outsourcing involves hiring third-party suppliers, often located overseas, to perform services or tasks over the Internet. Through digital platforms, buyers can connect with a large pool of remote suppliers, coordinate tasks among multiple suppliers, control quality, and pay the suppliers for professional services (Keuk et al., 2015). Some of the most popular online IT outsourcing platforms are Ariba Networks, Freelancer, Upwork, and CloudFactory. For instance, the Ariba network, the world's largest B2B digital platform, has more than 6.7 million businesses as buyers and suppliers, including over half of the Global 2000 companies (SAP Ariba network, 2023).

B2B digital platform is defined as "an inter-organizational information system through which multiple buyers and sellers interact electronically to identify potential trading partners, select them and execute transactions" (Rohm *et al.*, 2004). These B2B digital platforms are internet-based marketplaces where buyers and suppliers interact. They act as intermediaries and facilitate the transaction between buyers and suppliers in a platform, enabling the exchange of value alongside the information (Pavlou and Gefen, 2004).

In contrast to conventional marketplaces, B2B digital platforms ensure the accuracy of the information for buyers and suppliers (Guo *et al.*, 2021). In addition, by having access to the information of both parties prior to the establishment of their contractual relationship, B2B digital platforms can mitigate any disparities in information between the two parties.

B2B digital platforms not only help create a marketplace (Zhang et al., 2016) but also improve the performance of the supply chain by reducing transaction costs and promoting revisit for new opportunities (Liang et al., 2016). Platform-based marketplaces mainly rely on positive network effects for competitiveness and growth (Van Alstyne and Parker, 2016). To achieve the positive network effect, platforms focused on developing IT-based tools such as supplier recommendation systems, rating or feedback systems to attract buyers by providing more accurate information about suppliers and their service compared to traditional supply chain network (Koufaris and Hampton-Sosa, 2004). The network effect, in turn, brought more buyers and suppliers to the digital platforms and increased the frequency or volume of transactions (Pavlou and Gefen, 2004).

Either in digital or traditional marketplaces, supplier opportunism ruins the relationship between buyer-supplier and leads to the deterioration of buyers' profitability due to the extra cost induced by opportunism during the transaction (Wei et al., 2021; Zheng et al., 2019). In digital platforms, opportunistic behaviours can be exhibited by suppliers and buyers due to the information asymmetry and impersonal nature of virtual communication (Yoon et al., 2021). Due to this impersonality of communication, online interactions between buyers and suppliers also present new challenges in building trust between them (Pavlou and Gefen, 2004). Supplier opportunistic behaviour has long been one of the most studied topics (Goo *et al.*, 2007a; Lacity *et al.*, 2010; Poppo and Zenger, 2002; Ravindran *et al.*, 2015). A common approach to addressing behavioural uncertainty in outsourcing relationships is to draft a contract that anticipates all possible contingencies. However, this method can be resource-intensive, time-consuming for both parties, and may even result in opportunistic behaviour if the conditions become too complex (Hawkins et al., 2008). The dyadic trust mechanism is mainly researched as an alternative or supplement for a formal contract in the presence of uncertainties and opportunism in the relational exchange studies (S. J. Carson et al., 2006; Poppo and Zenger, 2002; Son et al., 2016).

1.2 Research Gap and Question

Relational exchange theory and social capital suggest that an informal mechanism using dyadic trust formed through repeated relationships and reputation acquired from various networks is effective in suppressing partners' opportunism (S. J. Carson et al., 2006;

Granovetter, 1985; Poppo and Zenger, 2002; Uzzi, 1996). Empirical findings in the strategic management studies suggest that a buyer firm is likely to choose either reputation or trust mechanism to deal with a different type of transaction uncertainty, and the choice helps organisations better meet their strategic need (Beckman et al., 2004; Gilsing et al., 2014a; Yamakawa et al., 2011). Previous research in relational exchange and strategic management has indicated that uncertainty and strategic needs play a significant role in shaping the dynamics of relationships (Beckman et al., 2004; Meuleman et al., 2010; Yamakawa et al., 2011). While some studies have compared the two types of partner-selection strategies (DiMaggio and Louch, 1998; Meuleman et al., 2010), they primarily focus on which strategy is preferred in different situations of uncertainty (Beckman et al., 2004; Gilsing et al., 2014b) or for different partnership goals (Capaldo, 2014; Yamakawa et al., 2011). This concept has been referred to as "environmental adaptation" in explaining partner selection strategies or tendencies. However, existing empirical studies, which focus on the impact of environmental conditions on strategic choices rather than exchange performance, do not provide a clear answer as to which strategy performs better. To answer this question, a comparison of the impact of external conditions on buyer performance for each partner-selection strategy is needed.

Similarly, the literature on B2B digital platforms has provided a wealth of information on the role of reputation systems, information quality, and cost advantages over traditional marketplaces (Bolton et al., 2004; Chakravarty et al., 2014; Zheng et al., 2019). Prior studies on B2B digital platforms have predominantly focused on their intermediary role based on IT-based feedback systems in the success of platform providers (Pavlou and Gefen, 2004; Wei et al., 2021; Zheng et al., 2019; Zhou et al., 2022). Moreover, research on partner-selection strategy does not address much about dyadic trust in B2B digital platforms, while the importance of reducing online transactional costs through repeated relations is emphasised for partnership success (Chien et al., 2012; Wei et al., 2021). The platform grows by attracting new customers and improving the profitability of both buyers and suppliers as customers to the platform providers (Parker 2016, Zhou et al. 2020). Therefore, in order for platform operators to attract hesitant buyers who outsource partners based on direct relationships and dyadic trust, platform providers must demonstrate to these buyers that they can consistently secure reliable suppliers at a low cost through the partner selection mechanism provided by the platform. However, the lack of knowledge on how attributes of B2B digital markets differently impact the performance of partnerships taking different partner-selection strategies limits our understanding of why reputation information has become a key strategy in the digital market. Buyers will continue their transactions on a platform only if the platform's partner selection helps improve business profitability and continuously enhance performance. The question of how a partner-selection strategy in B2B platforms can help buyers improve business profitability goes beyond just arranging transactions between suppliers and buyers, and this question has not been analysed in previous research (Zhou et al., 2022).

Transaction cost theory and relational exchange theory generally predict that repeating relationships based on trust will be cost-effective (Granovetter, 1985; Gulati, 1995; Uzzi, 1997; Yamakawa *et al.*, 2011). Finding new partners, negotiating, and signing contracts requires a lot of time and cost (Artz and Brush, 2000). Due to bounded rationality, contracts may not be exhaustive, and it is not possible to draft a contract that accounts for all potential scenarios and outlines measures for each party in those scenarios (Cao and Lumineau, 2015). Thus, the relationship governance strategy of choosing a partner based on trust can improve alliance performance in unpredictable situations (Poppo and Zenger, 2002). On the other hand, in a rapidly changing market, buyers are likely to seek reliable partners with new knowledge and expand their network (Beckman *et al.*, 2004; Gilsing *et al.*, 2014a). Otherwise, excessive dependence on existing partners can result in falling behind the competition in the changing market (Gulati, 1995; Uzzi, 1996). When the market can effectively convey the reputational information of suppliers, buyers will be able to efficiently find trustworthy suppliers (Hill, 1990).

Empirical findings in the studies of B2B digital platforms suggest that an appropriately implemented reputation system can improve the performance of buyers finding new partners (Chakravarty *et al.*, 2014; Pavlou and Gefen, 2004). However, the lack of studies comparing the performance of trust-based strategies leaves academic tension.

This study aims to contribute to relational exchange theory and B2B digital platform literature by systematically analysing the impact of market attributes and technological uncertainty on partnership performance by answering the following research questions.

- How do reputation- and dyadic trust-based partner-selection strategies perform in B2B digital platforms?

- What is the impact of information quality and information quantity on the performance of partnerships taking different partner-selection strategies?
- How does the uncertainty of technology affect the performance of the partnerships in B2B digital platforms?

B2B digital platforms differ from traditional markets by using information systems to overcome uncertainty about potential partners. Platforms help buyers gather and distribute information systematically, enabling them to assess and select new suppliers without prior experience. In partner-selection stage, the quality and quantity of information about potential suppliers are critical factors. However, there has been limited research on how informational factors influence partner selection mechanisms in B2B digital platforms. This study examines the impact of information quality and quantity on partner selection mechanisms by modelling them using the accuracy of reputation information and transaction volume within the platform.

This study posits that two attributes of B2B digital platforms, the quality and quantity of information, will have a differential impact on the performance of the partnerships taking a partner-selection strategy. There is a significant connection between the informational characteristics of a marketplace and the effectiveness of mechanisms that control opportunistic behaviour. B2B digital platforms serve as intermediaries in transactions between buyers and suppliers, setting them apart from traditional marketplaces (Pavlou, 2002). Platform operators use IT-based reputation management systems to gather and verify information about past transactions, helping buyer firms identify trustworthy suppliers (Chakravarty et al., 2014). Therefore, the correctness of shared information on past transactions plays a critical role in improving trust in the platform as an intermediary (Nosko and Tadelis, 2015a). This study highlights that the performance of a partnership can greatly vary based on the quality of information exchanged in the marketplace (Wiengarten et al., 2010). Furthermore, a B2B digital platform with a high number of participants enables buyers to access a wealth of market information and easily find suitable suppliers (Wei et al., 2021; Yoon et al., 2021). Additionally, frequent usage of the platform can improve performance by reducing transaction costs (Zhou et al., 2022). The study develops a model that incorporates the theories of transaction cost, relational exchange and reputation to analyse the impact of B2B digital platforms on partner-selection strategy and long-term transactional cost in the B2B digital plafroms.

1.3 Research Methodology

This study aims to investigate how the two informational attributes of B2B digital platforms (Information Quality and Transaction Volume) affect the configuration of supplier-buyer networks and alliance performance adopting different partner-selection strategies.

Answering questions related to the impact of market characteristics, types of competitive actions, and changes in market environments on the outcome of alliances presents significant challenges. Additionally, due to the virtual nature of the selection mechanism and the large number of participants involved, identifying the specific configuration of these networks through an empirical approach is not practically feasible. Thus, this study adopts a simulation-based approach to develop new theories as simulation models offer both powerful and flexible to examine the inherent dynamics of buyer-supplier network and their impact on the performance outcomes (Chang *et al.*, 2010).

The simulation model describes how buyer selection strategy dynamically shapes their supplier network and traces the performance varied by long-term acquisition cost and opportunism (penalty) costs. This study focuses, in particular, on the impact of different levels of Information Accuracy and Transaction Volume on the costs of buyer firms in outsourcing ITO partners in the presence of partner opportunism.

The effect of Information attributes of B2B digital platforms on the performance of buyers with different partner selection strategies may be dynamically emergent and nonlinear as buyers and suppliers constantly interact over a long-term period. This creates difficulties in isolating, observing, and accurately measuring the impact through empirical means.

With the simulation model, researchers can have full control over the conditions and variables, making it easier to isolate and study specific relationships with the resulting data from repeated experiments(Harrison et al., 2007). A simulation method allows a rigorous examination of the dynamic interaction within a buyer-supplier network under varying conditions (Hauser et al., 2017).

In this study, a model based on TCT, relational exchange, and social capital theory was proposed to simulate two distinct partner-selection strategies and analyse the resulting network configuration and performance to provide answers to the research questions.

With the computational model, buyers with different strategies interact with cooperative and opportunistic suppliers in a marketplace representing either a traditional supply chain network or a digital platform. Trust and Reputation as a partner-selection mechanism are modelled to moderate supplier opportunism by empirical findings and theories, relational exchange, social capital, agent theory and transaction cost theory. Two constructs which are the main question of this study: Information Accuracy and Transaction Volume, are discovered from the literature review in B2B digital platforms. As a result, this research attempts to provide an analytic explanation for the tension between the two types of partner-selection mechanisms in B2B digital platforms through a simulation approach. Furthermore, this approach is appropriate for addressing the research question in this study, as described in the previous section.

Furthermore, a simulation approach can combine both deductive and inductive characteristics (Harrison *et al.*, 2007). The process first derives a computational model from existing theories and assumptions deductively, then generates new findings from experiments to establish new theories inductively.

1.4 Thesis Outline

The document is structured as follows:

Chapter 1: Introduction
This chapter presents the background and motivation for the research. It outlines the research aim and objectives. The research territory and research methodology that shape the study are highlighted.

Chapter 2: Literature Review
The literature review is divided into three sub-sections. The first part deals with the opportunism of partners in business exchange, its causes and effects. The two types of uncertainties in ITO transactions are introduced. The second section focuses on the main question of this study, the reputation and dyadic trust mechanism as partner-selection strategies. The third section provides an overview of the context of B2B digital platforms.

Chapter 3: Methodology
This chapter provides an outline of the methods and procedures utilised in this research, along with a detailed explanation of the research philosophy and approach adopted in this study. The chapter includes a description of the simulation approach used in management

studies, along with a presentation of the experimental study's procedure. The section also provides a thorough discussion of the "Roadmap for developing theories with simulations," which was developed by Davis et al. (2007).

Chapter 4: Simulation Models

The simulation model of ITO partner-selection strategy in a buyer-supplier network is represented with a four-stage bidding procedure. The following sub-models are described in detail with equations in the section.

- Business Opportunities in the market
- Partner-selectin strategy
- Supplier opportunism and ITO uncertainties
- Rewarding Model and update of supplier information
- Model of Information Quantity and Information Quality

Parameters and measures for analysis are presented in the section of 4.3.

Chapter 5: Experiment and Results

This section describes simulation experiments and analyses the simulation results. Firstly, the base model is tested and validated against the relevant experimental findings. Then, the designed experiments are conducted to examine the effect of information accuracy and transactional volume (information quantity). Finally, the interaction effect of ITO uncertainties is analysed.

Chapter 6: Discussion

The effect of B2B digital platforms is discussed in accordance with simulation results. This section also discusses the theoretical contribution and managerial implications to the practitioners in ITO and B2B digital platforms.

Chapter 7: Conclusion, Limitations and Future Research

This section summarises the results. The limitations of the research are also discussed. Finally, several future research directions are proposed.

Chapter 2 Literature Review

Chapter 2 reviews bodies of literature related to the research questions. It begins with an overview of supplier opportunism, one of the most significant factors affecting the performance of supplier-buyer partnerships and raises questions for this study. The section reviews opportunistic behaviour and risks in the context of IT outsourcing based on the theories of transaction cost and agency. In the following section, the literature on trust and reputation as mechanisms to mitigate supplier opportunism is explored using relational exchange theory and social capital theory. This review highlights the roles of these two types of partner selection strategies in reducing uncertainty, which can lead to opportunism and hinder long-term performance. The fourth section examines the two main factors that differentiate B2B digital platforms from traditional markets, the quality and quantity of information and their impact on the performance of partners taking different partner selection strategies. Finally, based on these reviews, this section discusses the research gaps and motivates the research questions.

2.1 Supplier Opportunism and ITO uncertainties

Two key assumptions of transaction cost theory (TCT) are the assumptions of bounded rationality and opportunism. Thus, in inter-organizational exchange, there may be significant transaction costs due to bounded rationality and the threat of opportunism, which results in contracts that are designed to reduce risk and clearly define the terms of the exchange (Hawkins et al., 2008). Williamson (1975) defined opportunism as "a lack of candour or honesty in transactions, to include self-interest seeking with guile" and, as a result, "individuals will act in a deceitful, self-serving manner if given the opportunity" (Moran, 2005). In the ITO context, the opportunistic behaviour of suppliers is manifested as "withholding or distorting of Information, failing to fulfil promises and delivery of substandard products and services" (Goo *et al.*, 2007a). Supplier opportunism refers to an act or behaviour of an exchange partner for its own unilateral gains at the expense of its counterpart (Luo, 2007; Poppo and Zenger, 2002; Williamson, 1975). For example, when a buyer invites suppliers into a project, an opportunistic supplier may not deliver a promised level of development resources to the project as committed in a contract. The supplier tries to maximise its profits by channelling the saved resources to other projects.

The buyer, as the project ‘coordinator’, secures the necessary suppliers, forms a consortium and manages the execution and outcomes of the consortium to ensure that the results align with the initial plan by deploying the efforts of the contracted partners in a timely manner. In this study, the terms "buyer" and "coordinator" are used interchangeably depending on the context. The coordinator suffers damages such as the declined quality of the final product/service due to supplier opportunism. According to TCT, inter-organizational exchanges characterised by a high risk of opportunism necessitate pronounced resource expenditures to control and monitor the other party. Hence, the relative performance of outsourcing projects would be decreased (Hill, 1990; Parkhe, 1993). Opportunistic conduct can be penalised by contractual sanctions, loss of hostages or counteractions by the partner to appropriate added values (Hill, 1990).

Partner opportunism in an interfirm alliance is a multi-dimensional concept including several types of behaviours (Deeds and Hill, 1999). Hawkins (2007) summarises the cause and effect of opportunism in the alliance through literature research. The antecedents of opportunism can be described as dependent variables that influence the likelihood of opportunistic behaviour. The presence of dependence, uncertainty, and lack of formalisation is positively associated with opportunism, while relational norms and formalisation are negatively associated. In other words, the greater the dependence, uncertainty, and lack of formalisation, the more likely opportunistic behaviour is to occur, while greater relational norms and formalisation reduce the likelihood of an opportunism (Hawkins et al., 2008). The consequences of opportunism in a supplier-buyer relationship are negative impacts on performance and an increase in decision costs. Opportunism leads to weaker supplier chains, decreased innovation, lower satisfaction, and reduced profits. Moreover, the propensity of the supplier and the uncertainty of the environment were also found to influence the manifestation of supplier opportunism (Anderson, 1988).

Table 2-1 Antecedents and consequences of opportunism (Hawkins, 2008)

	Variables	Example
Antecedents of opportunism	Dependence (+/-)	Asset specificity (transaction-oriented investments)

(Independent variables)	Formalization (-)	Formal contracts, formalization of operational procedure
	Relational norms (-)	Solidarity, mutuality, flexibility, integrity
	Uncertainty (+)	Behavioural and environmental (volatility)
Consequence of opportunism (Dependent variables)	Performance (-)	Stronger supplier chain, innovation, satisfaction, profit
	Outsourcing decision	Acquisition strategy (make or buy)
	Decision costs (+)	Negotiation, quality monitoring, coordination failure

From a strategic perspective, the effect of opportunism on performance may be the most interesting relationship. Consequences of opportunism were represented through various performance indicators, such as success of outsourcing partnership (Wang, 2002), strategic fitness (Parkhe, 1993) and profitability (Nunlee, 2005). There was a negative relationship between opportunism and those performance indicators in these cases. Opportunism results in an increase in transaction costs according to TCT. Partner opportunism increases transaction risks and lowers the performance of partners in B2B alliances (Pathak et al., 2020).

Partner opportunism is linked to different types of uncertainty, technological uncertainty and measurement difficulty are particularly relevant for this study since these are two of the most widely studied transactional attributes in ITO literature (Kim and Chung 2003; Lacity et al., 2010). Firstly, Technological uncertainty is an exogenous uncertainty (Folta, 1998), which refers to "the inability to accurately forecast the technology sets that are required in future business opportunities by the market for the products of the alliance" (Perry et al., 2004). In ITO context, it is related to the definition of IS (Information Systems) requirements, emerging technologies, and/or environmental factors" (Lacity et al. 2010). Technological uncertainty would expose a firm to a problem raised by unforeseen changes; however, such exogenous uncertainty is generally beyond a firm's control (Folta, 1998; Poppo and Zenger, 2002). Therefore, when exposed to it, a firm tends to behave opportunistically, for example, limiting resources commitment to a joint project, to decrease its exposure to negative consequences such as a project failure (Folta, 1998; Luo, 2007). This would significantly impair the efficacy of contractual mitigation mechanism resulting in increase in partner opportunistic behaviours. Considering the nature of ITO industry, where the technology clock speed is fast, and such uncertainty poses a significant exchange hazard to buyer-supplier relationships (Poppo and Zenger, 2002).

Secondly, Measurement difficulty refers to the degree of difficulty in measuring the performance of exchange partner (Eisenhardt, 1989; Lacity *et al.*, 2010; Poppo and Zenger, 2002). Unlike technological uncertainty, measurement difficulty is task-specific, which arises when execution requires joint efforts with substantial time requirement (Eisenhardt, 1989). From agency theory perspective, it specifically refers to a situation, where a principal has difficulty in measuring the performance of its agency (Eisenhardt, 1989). Such difficulty has been linked with agent opportunism in the form of withholding resources commitment (Eisenhardt, 1989). Resulting information asymmetry will make it difficult for a principal to detect the agent defection, therefore, increases the chance of the agent behaves opportunistically (S. J. Carson *et al.*, 2006; Wathne and Heide, 2000).

In the perspective of B2B digital platforms where customers cannot interact physically with suppliers on a platform, they face further limitations in gathering information and communicating to evaluate performance. Opportunistic behaviours can be exhibited by suppliers and buyers due to this information asymmetry and impersonal nature of virtual communication (Yoon et al., 2021). Due to this impersonality of communication, online interactions between buyers and suppliers also present new challenges in building trust between them. Some researchers argue that digital platforms for B2B exchanges can reduce information asymmetry by improving transparency and efficiency (Breidbach and Maglio, 2016). On the other hand, other studies suggest that online B2B exchanges are exacerbated by the difficulty of assessing business partners' quality and commitment when compared to traditional channels (Chakravarty et al., 2014, Yoon et al., 2021).

In the ITO consortium, a buyer firm also faces the potential opportunistic behaviours of a supplier. For example, when a customer invites suppliers into a project, an opportunistic supplier may not deliver a promised level of development resources to the project as committed in a contract. The supplier tries to maximize its profits by channelling the saved resources to other projects. The coordinator suffers damages such as the quality of the final product/service declining because due to the lack of the amount of ‘opportunism’ committed by the supplier.

In an IT outsourcing consortium, a buyer firm is also susceptible to potential opportunistic behaviour from its suppliers. For instance, if a buyer as a consortium coordinator invites multiple suppliers to participate in a project, an opportunistic supplier may not provide the promised level of resources for the project as agreed upon in the contract. The supplier aims to maximize profits by redirecting the saved resources to other projects. The coordinator must take responsibility for the decrease in the quality of the overall project outcome caused by a single opportunistic supplier if it was not detected through proper monitoring during the project process.

This study suggests that firms, in the buyer's perspective, face both external uncertainties and behavioural uncertainties when they are engaged in a consortium for ITO projects on a B2B digital platform. External uncertainties come from the products and sectors being developed in the form of Measurement Difficulties and Technical Unpredictability (Lacity *et al.*, 2010). An interfirm alliance including ITO consortium is marred with the hazard of supplier opportunism with various uncertainties. Scholars found that such partner opportunism is prevalent in their empirical research in various types of outsourcing relationships such as Information Systems (Dibbern *et al.*, 2004; Handley and Benton, 2012; Kang *et al.*, 2016), logistics (Handley and Benton, 2012), and R&D (Carlson et al., 2006). Partner opportunism in an alliance can do serious economic and relational damage (Morgan et al., 2007) and it is one of the main causes of undesirable outcomes such as cost escalation and service degradation in information technology outsourcing (Handley and Benton, 2012).

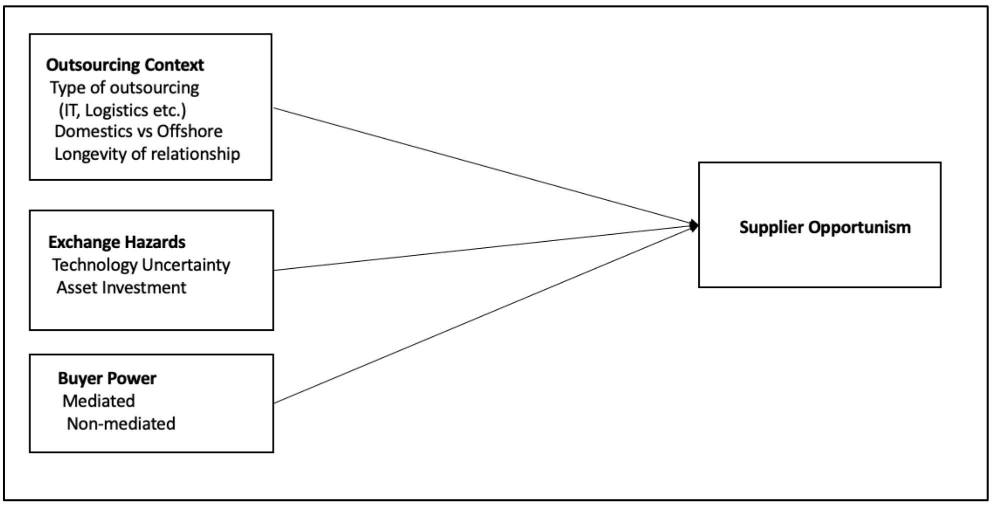


Figure 2-1 Opportunism model in the ITO relationship (Handley 2012)

2.2 Dyadic Trust and Reputation

2.2.1 Relational vs Structural embeddedness in buyer-supplier network

The prevention of partner opportunism is, therefore, one of the important factors for alliance success (Goo and Nam, 2007; Kim and Chung, 2003). A firm typically relies on a formal contract to mitigate the threat of partner opportunism (Artz and Brush, 2000; Cao and Lumineau, 2015; Poppo and Zenger, 2002). A contract is a statement of contractual parties' commitment or obligation for the performance expected as a result of an inter-organizational agreement (Macneil, 1980). Formal contractual mechanisms refer to written agreements and procedures that are enforced by the parties (Goo and Nam, 2007). Complex contracts have a greater number of specifications regarding the commitments, obligations, and resolution of disputes. These contracts have clearly defined roles and responsibilities, as well as procedures for monitoring and consequences for noncompliance, and the expected outcomes are specified (Poppo and Zenger, 2002). The presence of uncertainties related to the transaction, such as ITO-specific concerns, difficulty in measurement, and technological uncertainties, can lead parties to create more complex contracts (Poppo and Zenger, 2002). Since the process of drafting a complex contract requires the use of a firm's resources, such conditions are only employed when there is a high risk of contract breach (Goo and Nam, 2007).

An alternative to this is using a firm's own and others' social ties (or embeddedness) (Lumineau and Henderson, 2012; Poppo *et al.*, 2008). Such a mechanism is based on the notion that economic exchanges are embedded in a relationship (Deeds and Hill, 1999) and such embeddedness (or social ties) would act as an effective and cost-efficient alternative to a complex legal contract in the opportunism mitigation (Granovetter, 1985; Gulati, 1995; Oinonen *et al.*, 2018; Uzzi, 1997). Figure 2-2 shows that informal governance, along with formal contracts, plays an important role in dealing with market and partner uncertainties to generate improvement in the partnership. Relational embeddedness and Structural embeddedness are mainly researched as an alternative or supplement for high-cost formal contract in the presence of uncertainties and opportunism (S. J. Carson *et al.*, 2006; Poppo and Zenger, 2002; Son *et al.*, 2016).

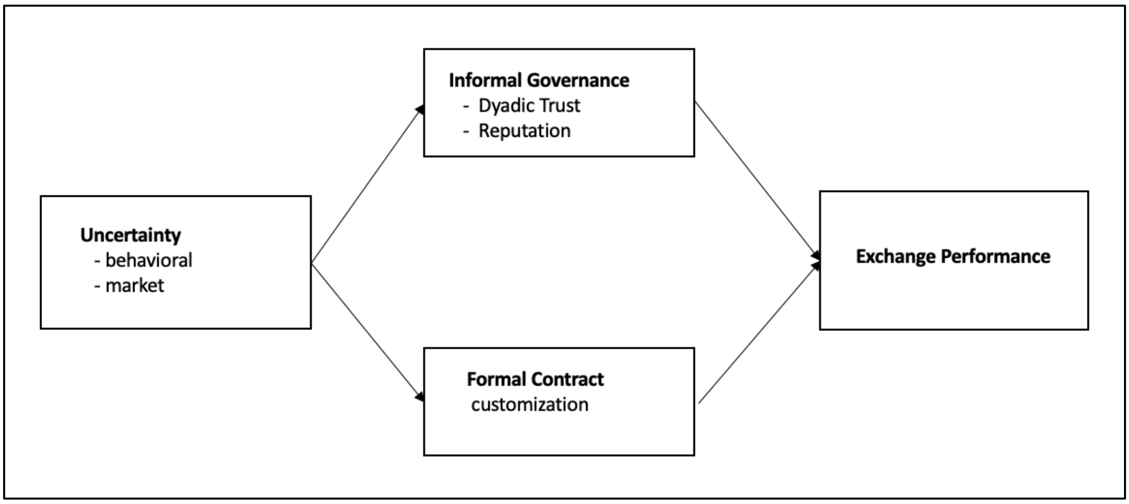


Figure 2-2 Informal governance on Exchange Performance (Poppo, 2002)

Trust

Two main strategies to restrain opportunistic behaviour of partners in strategic alliances include building a long-term relationship and finding a reputational supplier. Dyadic trust from the repeated relationship functions as an informal governance mechanism supplementing a contractual commitment (Rowley et al., 2000) in mitigating partner opportunism in following ways. Firstly, the main outcome of positive interactions is an accumulation of goodwill and trust (Granovetter, 1992; Son et al., 2016). Similarly resulting outcomes such as commitment and obligation would serve to uphold agreed norms of interaction reducing partner opportunism (Granovetter, 1992; Perry et al., 2004). Secondly, positive interactions in the past would increase parties' expectations of the continuity of their relationship. Such expectation of continuity reduces partner opportunism (Nooteboom, 2016) since it encourages the relationship to look at the long-term return (Poppo and Zenger, 2002).

Various advantages can be enjoyed by exchange parties who are coupled through relationally embedded ties. Firstly, Uzzi (1997) argues the relational alliance can benefit from mutual trust, fine-grained information and joint problem-solving. Secondly, opportunistic behaviour is effectively controlled in trust-based transactions. The sharing of fine-grained information dramatically reduces exchange risks which threaten outcomes. Complex problems and conflicts are smoothly resolved through collaborative efforts. In line with this research, it is also claimed that transaction risks are noticeably decreased by flexibility, solidarity and information sharing between relationally embedded firms (Poppo and Zenger, 2002). Flexibility enables them to respond effectively to unpredictable events. Solidarity encourages their joint problem-solving activities. Information sharing facilitates the flexible response to unpredictability and joint problem-solving through solidarity. Thirdly, from the perspective of cost-effectiveness, firms can cut the considerable transaction costs of finding and managing new partners by repeating or maintaining their current transaction relationships (Goo *et al.*, 2007).

Repetitive ties to the same network partners can reduce the flow of new or novel information into the network because outside members who can contribute innovative ideas are few or non-existent (Uzzi, 1997). Under these conditions, firms become reluctant to seek innovative technology beyond their pools of partners and leave them locked in the closed partner network (Gulati, 1995), the alliances will be unable to respond to the demand of markets, eventually leading to a decline (Uzzi, 1997).

Reputation

While Trust acts as a mitigation mechanism at the dyadic level, 'Reputation' works at network level (Granovetter, 1985; Hill, 1990) as social capital of a partner. Social capital is defined as "resources embedded in a social structure which are accessed and/or mobilized in purposive actions" and hence its concepts include "three elements intersecting structure and action: the structural embeddedness, opportunity accessibility and action-oriented use aspects" (N. Lin, 1999). Moreover, the most common conceptualisation of social capital is regarded as reputation in a network (Moran, 2005).

In B2B digital platforms, a firm's ratings represent its reputation which is an indicator of past performance and a predictor of future behaviour (Gopal and Koka, 2012). For example, a potential supplier with accumulated positive ratings in a network would signal the others its reliability as a partner (Borgatti and Foster, 2003), which is measured based on the collective evaluation of its exchange partners counterparties with whom it has a transaction in the network.

For this reason, by checking a potential partner's network position, a buyer firm can reduce the chance of selecting untrustworthy partners. At the execution stage in the simulation model, if a partner behaved opportunistically in a transaction, negative information would be shared across a network and damage its reputation (Rowley et al., 2000). Therefore, a reputational partner (e.g., a high level of network centrality) would refrain from behaving opportunistically because the damage to its reputation caused by such behaviour is proportionally larger than those with a lesser degree of reputation (Kandori, 1992).

The contingent nature of Trust and Reputation is often found in the strategic studies of partner-selection strategy: exploitation (of dyadic trust-based relation) vs exploration (of reputational suppliers) and has been discussed in the relevant literature as follows. Beckman (2004) argues that the nature of the uncertainty is a driving criterion for firms in choosing their partner-selection strategy (Figure 2-3). For example, firms are likely to rely on the existing relationship with old suppliers when market-level uncertainties are external and shared across firms. Market-wise difficulties in predicting demand and input costs make firms reinforce the trust-based relationship. Alternatively, if a firm enters a new market with innovative technology, the organization faces a firm-specific uncertainty of the chance of successful development and marketability and takes a strategy to explore new partners and share the risk. New partners broaden the scope of the firm, increasing the likelihood of obtaining new information and of adding to the diversity of information to which a firm is exposed.

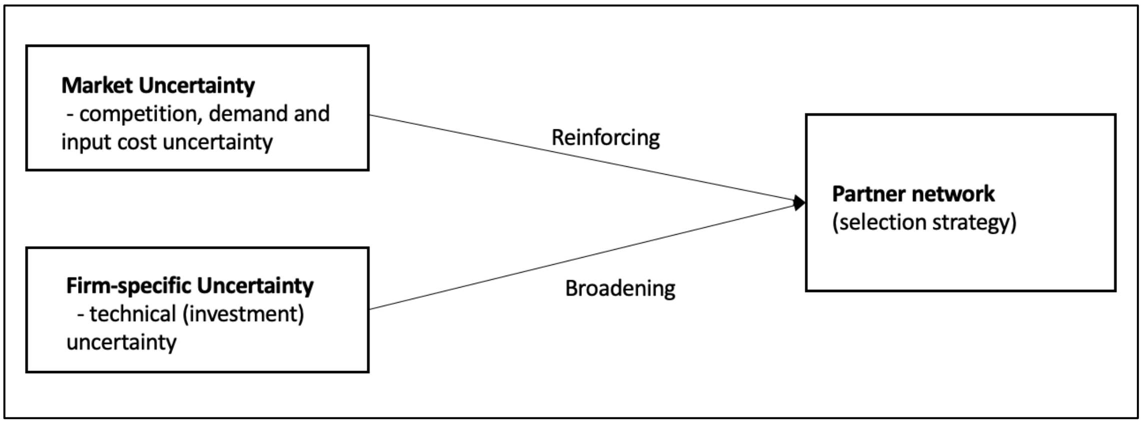


Figure 2-3 Uncertainty – Selection strategy (source: Beckman, 2002)

The research of Yamakawa (2011) suggests that the relationship between firm performance and alliance strategy can be moderated by various factors, firm characteristics, strategic orientations, and the industry environment the focal firm faces (Figure 2-4). The findings suggest that trust-based exploitation selection can be more beneficial to the performance of an alliance when pursuing a cost leadership strategy, as firms tend to focus on efficiency and cost-saving in collaboration while minimising their expenses for searching and negotiation efforts. On the other hand, a differentiation strategy requires a constant search for new technologies to differentiate itself from competitors.

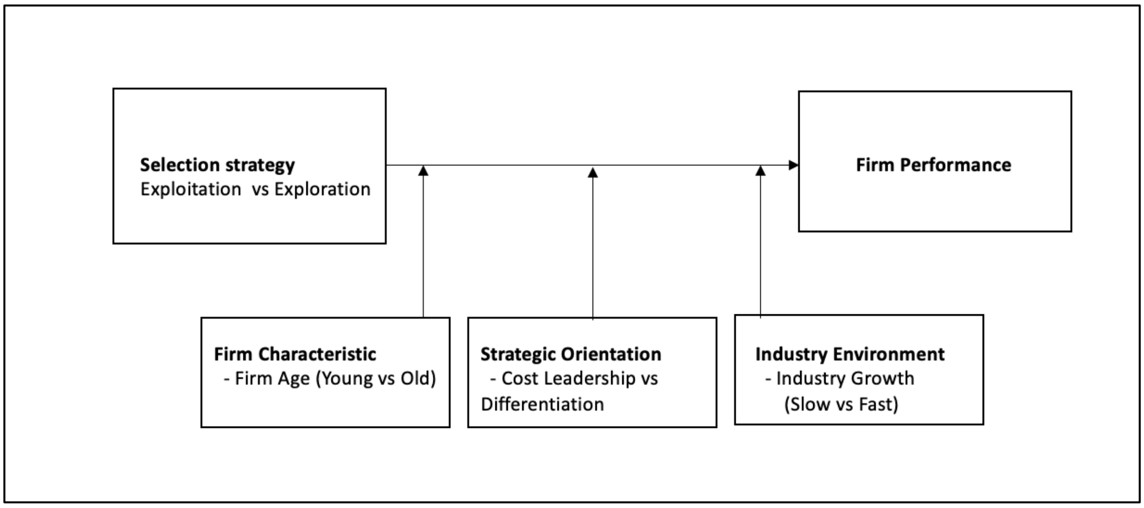


Figure 2-3 Selection strategy vs Performance (source: Yamakawa, 2011)

Gilsing (2014) reports a boundary condition of a relation-based strategy which can be less beneficial or problematic when market faces technological unpredictability. By the boundary condition, the study suggests that the explorational capacity to find new partners without relying on past success or sustained relationships is one of the key factors for success in IT innovation, where technological unpredictability is high. Similarly, Meuleman (2010) reveals that in situations of low opportunism as a boundary condition for relational embeddedness, a reputational partner-seeking strategy can replace a trust-based selection strategy.

These empirical findings support the importance of organizational, strategic, and environmental fit in relation to a firm’s partner-selection strategy and its performance consequences in the context of linear supply chains where the information of new partners is transmitted through a decentralised network of market participants.

2.2.2 Reputation System vs Dyadic Trust in B2B digital platforms

Prior research has shown that informal control mechanisms on B2B platforms can strengthen trust, reduce risks, and promote cooperative norms (Hong and Pavlou, 2017; F. R. Lin et al., 2005; Pavlou, 2002). Online reputation serves as a feedback mechanism that moderates supplier opportunism on digital platforms (Bolton et al., 2004). A feedback-based reputation system is widely used by major online marketplaces. This system promotes indirect reciprocity, fostering longer relationships and contributing significantly to the success of digital marketplaces. In contrast, in traditional markets, partners tend to repeatedly choose the same partners, leading to "direct reciprocity" and reducing opportunistic behaviour (Bolton et al., 2004).

Digital platforms facilitate the creation of institutional marketplaces, providing buyers and suppliers with a means of finding partners and ensuring online inter-organizational exchange despite the uncertainty surrounding online transactions and new partners without prior relationships. Pavlou and Gefen (2004) suggest that the trust in the platform, which is developed through the feedback system, has a positive impact not only on reputable suppliers, but also on all suppliers on the platform. In B2B digital platforms, intermediary systems, such as feedback systems, increase buyers' trust in the marketplace, decrease the perceived risk associated with unfamiliar suppliers, and facilitate online transactions. Trust in a new supplier on these platforms is a "calculus-based credibility," generated without prior relationships through the use of IT-based feedback systems (Ba and Pavlou, 2002).

The reputation thus formed discourages the opportunistic behaviour of the supplier. For example, on most platforms, the supplier's reputation is quantified and marked through the reputation system, and these ranks act as a powerful means of control within the community (Zheng *et al.*, 2019). In other words, suppliers with higher ranks tend to refrain from opportunistic behaviours (Ba *et al.*, 2003; Zheng *et al.*, 2019). Other researchers have reviewed practical limitations. Nosko (2015) argues that buyers often leave without giving feedback if the project with a supplier they first found through the platform was not good. In this case, the platform's feedback system is biased more positively than it actually is because negative reviews are not fully reflected.

Furthermore, an efficient reputation system necessitates the acquisition of high-quality information about a supplier and its services from multiple perspectives. The quality of information is also impacted by the ability of the person responsible for providing feedback at the client company after the project is completed (Dikow et al., 2015). For instance, if a contract manager is tasked with entering the post-evaluation of the supplier, it can be challenging for non-technical staff to professionally evaluate all aspects of service quality, including the communication between developers during project execution and the deliverables provided.

Researchers maintain that the reputation information system for suppliers is crucial in fostering trust in both the platform as a marketplace and the suppliers within it (Bolton et al., 2004; Chakravarty et al., 2014; Pavlou and Gefen, 2004; Yoon et al., 2021). In particular, the performance of buyers firms in platforms is influenced by the quality of information (Wiengarten et al., 2010) and the correctness of the information (Nosko and Tadelis, 2015b) provided within platforms. While many studies have explored the role and impact of reputation, this one-sided focus raises the question of why reputation mechanisms are so popular in B2B digital platforms. There have been few studies that have simultaneously compared the performance of dyadic trust and reputation mechanisms in B2B digital platform literature. To the best of our knowledge, this study is the first to aim to systematically analyse the relative performance of the two strategies as competing mechanisms in B2B digital platforms.

Furthermore, this study posits that the performance difference in the partner-selection strategy is influenced by information accuracy and transaction volume across different marketplaces. The study proposes a model in which buyers are impacted differently by the level of Information Accuracy and Transactional Volume.

2.3 Information Quality and Quantity in B2B digital platforms

This study argues that the two distinctive attributes that exhibit the difference between B2B digital platforms and traditional marketplaces in terms of performance of partner-selection strategies are information accuracy and transaction volume (Gefen and Carmel, 2008; Van Alstyne and Parker, 2016; Zhou et al., 2022).

2.3.1 Information Accuracy (Information Quality)

The efficacy of the reputation strategy will be enhanced by the effective flow of information in the supply chain (Hill, 1990). When a reputation mechanism is properly implemented, buyers will be able to accurately assess the likelihood of a successful collaboration, even without prior experience with a particular supplier. Inefficiencies in the transmission of this information can lead to uncertainty for the buyer who selects a supplier based on the reputation information provided by the marketplace (Nosko and Tadelis, 2015a). As an intermediary between enhanced transaction activity, these IT-enabled feedback mechanisms provide a certain degree of guarantee and protection for transactions by restricting the ability of a seller to engage in opportunistic behaviour (Bulut and Karabulut, 2018; Lu et al., 2016). Bulut et al (2018) describe feedback mechanisms as buyer-driven reputation mechanisms that gather and disseminate information and electronic word-of-mouth (eWOM) behaviour and performance. By allowing buyers to evaluate the entire seller community, feedback mechanisms should act as informal buyer-driven certification systems for sellers. In digital platforms, the quality of buyer and supplier information is ensured by the platform providers, as they transparently collect the reputation of all participants before the relationship is established (Guo et al., 2021). As Information Systems facilitate the collection, processing and distribution of reputation information, the quality of reputation information depends on the design, functionalities, efficiency and effectiveness of IS adopted by B2B digital platforms as well as the user's expertise and motivation (Dikow et al., 2015).

According to the research of (Bulut and Karabulut, 2018), both the quality and quantity of electronic word-of-mouth (eWOM) positively influence trust and buyers' intention to use digital platforms. This research postulates that the quality and quantity of information, two attributes of B2B digital platforms, will have a varying impact on the efficacy of the partner-selection strategy (Wiengarten et al., 2010). There is a marked correlation between the informational characteristics of a marketplace and the efficiency of mechanisms that curb opportunistic behaviour. B2B digital platforms act as intermediaries in transactions between buyers and suppliers, setting them apart from traditional marketplaces (Pavlou, 2002). The platform operators utilise IT-based reputation management systems to gather and authenticate information regarding past transactions, assisting buyer firms in identifying reliable suppliers (Chakravarty et al., 2014). As a result, the accuracy of shared information on past transactions is a critical aspect in enhancing trust in the platform as an intermediary (Nosko and Tadelis, 2015a).

Online feedback information has become increasingly reliable thanks to the implementation of IT-enabled detection based on machine learning technology, which was not available in traditional supply chains. (Chatterjee, 2001; Zhang et al., 2016). In a digital marketplace, buyers have access to precise information about the conduct of prospective suppliers, which reduces the cost of preventing opportunistic behaviour and enhances the buyer's profitability (Liang et al., 2016). On the other hand, the dissemination of reputation information in traditional markets is assumed to occur via a word-of-mouth mechanism, with multiple intermediaries between the buyer and supplier. The accuracy of the information is assumed to vary based on factors such as the WOM network structure (Shuang, 2013) and communication channel (Berger and Iyengar, 2013). Although the performance of partnerships can vary greatly depending on the quality of information exchanged throughout the supply chain (Wiengarten et al., 2010), there has been limited research on the impact of informational quality on the performance of buyers in terms of supplier-selection strategies.

Thus, the objective of this study is to examine the effect of the quality of information transmitted in the marketplace on the performance of buyer groups who employ two partner selection strategies.

2.3.2 Transaction volume (Information Quantity)

Digital platforms typically facilitate a much larger number of transactions than traditional marketplaces, due to the ease of accessibility, scalability, and low transaction costs offered by the digital platform. Additionally, the global reach of digital platforms makes it possible for businesses to connect and engage with a wider range of customers and suppliers, thereby increasing the volume of transactions (Wei et al., 2021; Zhou et al., 2022). This can result in an increase in competition and bargaining power, which can drive down prices and increase the efficiency of the supply chain. The sheer volume of transactions on digital platforms can also generate large amounts of data that can be used to optimize supply chain operations and make informed business decisions (Akter and Wamba, 2016).

Generally, transactions with high transaction costs should be internalized through vertical integration based on the transaction cost theory (Williamson, 1975). In traditional supply chains, this leads to a correlation between higher cumulative costs and a greater number of transactions. However, the effect of transaction frequency in platform transactions may differ from those in traditional supply chains. With more frequent transactions on a given platform, buyers become more skilled in searching, processing information, and completing deals (Wei et al., 2021; Zhou et al., 2022). For buyers who complete more transactions, automation and artificial intelligence can further shorten the learning curve and ultimately save time and money (Davenport et al., 2020). The platform has a greater advantage in reducing transaction costs when there is a higher number of transactions among buyers occurring.

A B2B digital platform offers an infrastructure to facilitate buyer–supplier interactions in a two-sided market (Chakravarty et al., 2014) and allows firms to access more business opportunities at a lower cost compared to traditional markets (Hong and Pavlou, 2017). As firms become more reliant on these platforms, they are increasingly using them to outsource IT technology suppliers and form consortia. B2B digital platforms mainly rely on positive network effects for growth (Parker et al, 2016). To achieve this, platforms have focused on developing IT-based tools such as supplier recommendation systems, rating or feedback systems to provide more accurate information on suppliers and their services than traditional supply chain networks (Koufaris and Hampton-Sosa, 2004). This network effect, in turn, attracts more buyers and suppliers to the platform, increasing the frequency and volume of transactions (Pavlou and Gefen, 2004). As transactions take place in the online market, more information about buyers and suppliers becomes available, providing valuable data for the decision-of supplier choice (Akter and Wamba, 2016). The two factors Interact holistically; for example, increased trust and lower acquisition costs attract more customers, which in turn increases business opportunities and attracts other suppliers.

Table 2-2 Attributes of B2B digital platforms vs Traditional markets

Study	Attributes of B2B digital platform	Causal relations
Bolton (2004)	Information of past service quality	Feedback system -> trust (indirect reciprocity)
Ba and Pavlou (2002)	Trust-building technology	Feedback system-> trust (calculus-based credibility)
Zheng and Xu (2019)	Supplier reputation (social ranks)	Reputation -> (-) opportunism
Chakravarty (2014)	Correctness of the shared information (of suppliers)	Accuracy -> reputation mechanism
Nosko (2015)	Better reputation mechanism (accuracy in the information)	Accuracy -> benefit of platform (identifying and promoting higher quality seller)
Pavlou and Gefen (2004)	Improved IT-based feedback system	Efficiency -> trust & volume

Wei (2021)	Large number of participants (opportunities)	Volume -> (+) trust and (-) cost (efficient and low cost in searching suitable suppliers)
Zhou (2021)	Transaction frequency (as moderator)	Frequency -> (+) trust on suppliers, (-) transaction cost

2.4 Summary

This section, through a review of the literature, examines relevant studies in B2B digital platforms and posits that information quality and quantity are critical factors in determining why reputation mechanisms are more prevalent than trust mechanisms in partner selection strategies within B2B digital platforms.

Table 2-2 summarises previous research on the relationships between key constructs that represent the differences between B2B digital platforms and traditional markets. These relationships form the basis of the simulation model in this study.

This chapter focused on identifying the crucial aspects of partner selection mechanisms and B2B digital platforms from relevant literature. Researchers in the fields of relational exchange and social capital have long explored how informal mechanisms such as dyadic trust or reputation can enhance exchange performance by mitigating partner opportunism. Additionally, strategic management studies have demonstrated that companies tend to continue their trust-based relationships with familiar partners or seek out reputational partners beyond their existing networks in order to address uncertainties or achieve their goals. Scholars in both disciplines have generally agreed that each mechanism, trust or reputation, is preferred for its own advantages in dealing with certain uncertainties. However, in B2B digital platform research, instead of comparing the two mechanisms, there is a phenomenon of focusing on the role of the reputation-based mechanism.

The findings form the basis for outlining the models of partner selection strategies, buyers' behaviour, environmental uncertainties, and performance evaluation, as to be described in this next section.

Chapter 3 Methodology

Chapter 3 describes the methodology of this study. It involves the research philosophy and research approach underpinning this simulation method adopted to gain a deeper understanding of the significance of reputation and trust as factors in choosing partners in B2B digital platforms.

This study examines the impact of two key attributes of B2B digital platforms on the formation of supplier-buyer networks and alliance performance by two partner-selection strategies. The simulation model depicts how the buyer's selection approach shapes their supplier network and how performance changes in terms of partner acquisition and opportunism. It specifically focuses on the effect of varying levels of information accuracy and transaction volume on the costs of outsourcing ITO partners for buyer firms in the presence of opportunistic behaviour. The influence of information attributes on the performance of buyers adopting different partner selection strategies may be complex and nonlinear as buyers and suppliers continuously interact over time. This presents difficulties in observing and measuring the impact empirically. A simulation approach, however, can assess the dynamic interaction within a buyer-supplier network and its impact on transactional costs under varying market conditions, overcoming the challenges of obtaining empirical data regarding the unique challenges faced by ITO partnerships.

This study follows the simulation-based theory development process prescribed by Davis et al. (2007). The next section explains "the roadmap for developing theories with simulations" developed by Davis et al. (2007). This process is used as a guideline for the research approach in this study.

3.1 Research Philosophy

The selection of research methodology depends on the research philosophy that guides the research procedure. According to Collis and Hussey (2014), a research philosophy serves as a guide for conducting research based on beliefs about reality and knowledge (Collis and Hussey, 2009). The main philosophies are positivism and interpretivism, which reflect distinct perspectives on how humans understand the world.

Positivism is a scientific approach that emphasises empirical, quantitative data and objective analysis. It assumes that there is a single reality and that this reality can be studied objectively and independently of the researcher. This approach views the world as being orderly and predictable, and it aims to develop universal laws and theories (Hudson and Ozanne, 1988). Consequently, they carry out their research in a systematic and organised manner by defining a precise research theme, forming suitable hypotheses, and utilising an appropriate research technique (D. Carson et al., 2001). Positivist researchers maintain a detached stance from the research participants, which helps them maintain emotional objectivity and differentiate between reason and emotion (Carson et al., 2001).

Interpretivism, on the other hand, is a more subjective approach that emphasises the interpretation of meaning and experiences. It assumes that reality is constructed through our perception of it and is shaped by our beliefs, values, and culture. This approach views the world as complex and multi-faceted, and it aims to understand the subjective experiences and perspectives of individuals (Hudson and Ozanne, 1988). Interpretive researchers steer clear of inflexible frameworks, as seen in positivist research, and instead embrace a more personalised and adaptable research structure (D. Carson et al., 2001). This approach enables them to capture the meanings inherent in human interaction and to interpret what is considered reality (D. Carson et al., 2001). They view the researcher and their sources of information as interdependent and engage in mutual interaction (Hudson and Ozanne, 1988).

Simulation as a research approach can be considered a form of positivism, as it typically involves the use of quantitative methods and computational models to analyse and test theories and predictions (Eldabi *et al.*, 2002).

In this study, simulation involves creating a model of a real-world system, that is a supplier-buyer network resembling B2B digital platforms, and then using that model to reveal an underlying mechanism by analysing the performance of buyers differentiated by their choice of partner-selection strategy. It relies on the assumption that the model accurately represents the marketplaces and that the outcomes made from the model can be objectively verified. This approach is consistent with the positivist philosophy, which emphasises qualitative data, objective analysis, and the search for universal laws and theories (Hudson and Ozanne, 1988).

3.2 Research Approach

Research has been traditionally conducted through two main approaches: "theoretical analysis or deduction, and empirical analysis or induction" (Harrison et al., 2007).

An inductive approach to research differs from a deductive approach in that a deductive approach is concerned with testing theories, whereas an inductive approach seeks to generate new theories based on the data collected. Inductive approaches use research questions to narrow the scope of their studies, while deductive approaches begin with a hypothesis. A deductive approach focuses on causality, while an inductive approach generally focuses on discovering new phenomena or examining previously researched phenomena from a different perspective. Qualitative research is generally associated with inductive research, whereas quantitative research is most commonly associated with deductive approaches. However, there are no set rules, and some qualitative studies can have a deductive orientation. For example, a grounded theory method, pioneered by (Glaser and Strauss, 2017) is a specific inductive approach. Grounded theory is a research approach that involves creating a theory that is grounded in collected and analysed data. Social processes, such as relationships and behaviours between groups, are examined using this method. Inductive approach has been modified and employed to confirm the hypothesis developed from a deductive study (Harrison *et al.*, 2007).

There are own weaknesses in both inductive and deductive approaches. The problem with deductive approach is that the conclusions can only be true and supported if all the propositions suggested by inductive research are true and all the terms are clear. This is a significant weakness in deductive reasoning. It is based heavily on the initial propositions being correct, so if any of them are incorrect, the theory is considered invalid and unsound. This approach assumes, for example, that all disciplines in natural science work similarly, but they don't. For the inductive approach, the availability of data is a major problem with empirical research. The problems are compounded by the need for comparable measures across a sample and, in the case of dynamic analysis, across an extended time period when variables such as secret agreements are unobservable or difficult to measure. Consider the chances of collecting reliable data on subunit power from a sample of organizations over a long period of time. In addition to this, inductive approach begins with a single observation, or an inference drawn from very specific and similar situations. In a diverse world, this cannot always lead to an accurate inference.

Thus, these assumptions often do not have any real-world relevance for their own usefulness (Harrison et al., 2007).

Simulation approach can overcome these problems by producing virtual data and making more realistic assumptions. Therefore, deductive and inductive characteristics are both present in simulation approach (Axelrod and Hamilton, 1981). A simulation model is deductive since it is derived from existing theories and assumptions. Alternatively, it is inductive because new findings are inferred through simulation experiments. With these two characteristics, a simulation approach proved useful. Simulation method can capture analytical reflections via mathematical models, which provide their own virtual data to overcome the problem of data availability in empirical studies (Harrison et al. 2007). Researchers conduct such research by modelling and transforming real-world problems into a virtual world (i.e., simulation) in order to gain meaningful insights into the problem.

This study is focused on an inductive approach, as it constructs a simulation model to explore the effectiveness of two partner-selection mechanisms in B2B digital platforms and proposes new explanations based on the results (Figure 3-1). The simulation model is designed to analyse data and identify patterns and relationships in the data, which are used to generate new hypotheses and theories (Harrison *et al.*, 2007). While the inductive approach is commonly associated with interpretivism, it is not limited to this paradigm and can be used within a positivist framework to develop propositions , as demonstrated in studies such as (J. Lee et al., 2003; N. Li et al., 2015; Y. Li et al., 2021).

Simulation-based research requires a mechanism-based explanation of the investigated phenomena in many cases (Beese *et al.*, 2019). Simulations rely on mechanism-based explanations, often expressed as models–- constructed abstractions that describe simulation behaviour and resemble real-world phenomena. Simulation models require researchers to hypothesise and detail hidden causal mechanisms, also such abstractions are not always simplifications (Frank *et al.*, 2014). Mechanism-oriented modelling is suitable for studies that try to explain why a certain strategy enjoys a leading position in the market as a network mechanism, such as this study.

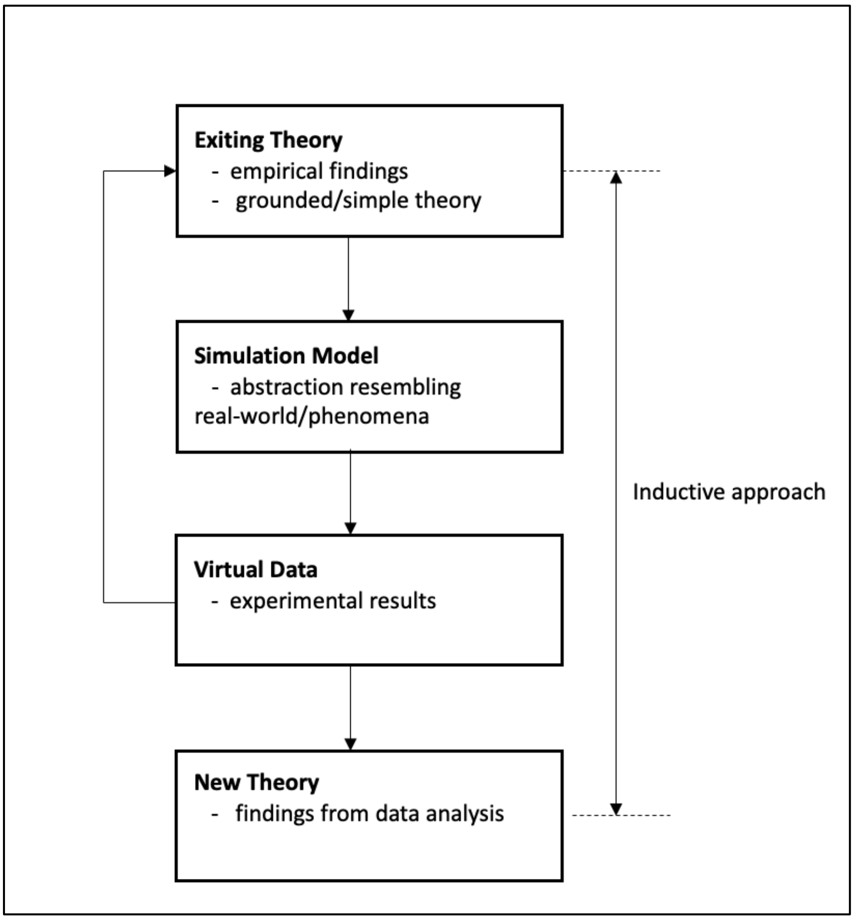


Figure 3-1 Research approach using simulation method (Davis et al, 2007)

The simulation approach is recommended for solving research problems involving interconnectedness, nonlinearity, or circular causality. Then, a simulation study is conducted using existing theories and empirical studies that provide theoretical foundations and empirical evidence for internal and external validity. Based on the results of the simulation experiment, new theories are developed, or existing theories are extended. Additionally, further empirical research may be conducted to verify a newly developed or extended theory.

A simulation study is evaluated based on its contribution to the literature according to Davis et al. (2007).

- Does the research question derived from its related existing theories have its theoretical consistency with them?
- Do the simulation experiments focus on the development of a new theory or on the extension of an existing theory?

This study examines the disproportional performance gain for Trust and Reputation mechanism in the following research setting. There are multiple coordinators and suppliers in an ITO network. They establish ITO consortia in response to given outsourcing opportunities with different levels of uncertainty. The formation of a consortium is viewed as an interaction between coordinators and suppliers to gain their profits. Then, as they continuously interact with one another, dyadic and network trust are generated and reinforced, and their behaviours and/or outcomes become more interrelated. Therefore, this research includes the behaviour of market participants who compose a marketplace and affect one another through their interactions and the performance which is the consequence of their behaviour. Furthermore, the two types of partner-selection strategies are compared in the settings between digital vs traditional marketplaces in the long-term perspective. As a result, a simulation approach is appropriate for this study.

3.3 Simulation Methods for Developing Theory

Research in this study was conducted using the roadmap for developing theories with simulation" (Davis et al., 2007), which is a generic method of conducting research. (Davis et al., 2007). Table 3-1 shows how research approach in this study proceeds based on the roadmap.

Table 3-1 Simulation roadmap guided by Davis et al. (2017)

	Guideline (Davis 2007)	Research Approach (this study)	Chapter
Step 1	"Begin with research question & simple theory"	Literature Review Find research gap & define research question	2
Step 2	Choose Simulation method	Research Approach	3
Step 3	Create computational representation	Simulation Models	4
Step 4	Verify computation presentation	Design simulation experiment Conduct basic test and verify models	5.1

Step 5	Experiment to build novel theory	Conduct experiments to compare two strategies	5.2 – 5.7
		Discussion Findings	7
Step 6	Validate with empirical data	Limitation	7.3

3.3.1 Begin with research question and simple theory

According to the roadmap, simulation studies need to begin with a research question that reflects a deep understanding of existing literature and relates to a significant theoretical issue (Weick, 1989). Simulation research without such a question becomes a random walk in which the researcher lacks focus and theoretical relevance and risks becoming overwhelmed by computational complexity. Simulation research without such a question may risk becoming an overwhelming amount of computational complexity without focus and theoretical relevance.

In addition to focusing on intriguing and theoretically relevant research questions, simulation is particularly useful to the theoretical development of simple theory.

> Simple theory is an "undeveloped theory that involves a few constructs and related propositions with some empirical or analytic grounding but that is limited by weak conceptualization, few propositions, and/or rough underlying theoretical logic" (Davis, 2007, p,.485).

The role of simple theories in research can also be evident in the inclusion of concepts and basic processes from well-known theories (e.g., competition and imitation), especially if the focus is on their vaguely understood interrelationships. If the simulation study is theoretically disconnected from existing literature, it will primarily focus on computational representations. The roadmap recommends that, like other approaches, studies using a simulation approach should begin with a clear and concrete definition of a research question derived from a thorough literature review, which also involves theoretical considerations.

Chapter 2 reviewed the existing literature concerning the concepts and roles of Trust and Reputation to overcome partner opportunism in the context of ITO transactions. In addition to this review, this chapter explored the comparison between a market in which information is centralized by an IT-based platform and a traditional market in which information is shared through a network among members. Through this comprehensive literature review, the research questions of this research were drawn as in the section 1.2.

Trust and Reputation as partner-selection strategies are supported by relational exchange theory and social capital theory respectively. Their effect on partner-opportunism is modelled by the findings from related studies, agent theory and transaction cost theory. Two constructs which are the main question of this study: effect of Information Accuracy and Transaction Volume are discovered from literature review in B2B digital platforms. As a result, this research attempts to provide an analytic explanation for the tension between the two types of partner-selection mechanisms in B2B digital platforms based on the above simple theories through a simulation approach. Furthermore, this approach is appropriate for addressing the research question in this study as described in the previous section.

3.3.2 Step 2: Choose simulation method

Selecting a simulation approach should also be determined by the fit of the research question, assumptions, and the conceptual logic of the simple theory with those of the simulation approach. This approach should be carefully determined because the simulation approach can impose a theoretical logic, nature of research question, and boundary conditions.

Davis (2007) suggests five simulation approaches: systems dynamics, NK fitness landscape, genetic algorithms, cellular automata, and stochastic processes. NK fitness landscape, genetic algorithm, and cellular automata methods can be categorised as agent-based simulations (Za *et al.*, 2018). Agent-based simulations are able to model a real scenario creating artificial worlds. Automated agents are used to populate these scenarios and simulate the behaviour of their real-world counterparts to validate theoretical and empirical constructs (Druckenmiller and Acar, 2009). Table 3-2 shows the comparison of the methods, which is extracted from the table in the research of Davis et al. (2007).

In the first four methods, there are specific research questions, assumptions, and common experiments that are applicable to them. Stochastic processes, on the other hand, are a set of simulation methods that are tailored for specific domains and include probabilistic sources, which are a form of simulation. Therefore, this method is recommended when the research questions, assumptions, and common experiments in a certain simulation study does not correspond to those in the four standardised methods. Further, all the assumptions, research questions, and experiments used in the first four methods are standardised. Stochastic processes, on the other hand, are merely another name for simulation methods based on probabilistic sources and tailored to a particular domain. When assumptions, research questions, and experiments used in a simulation study differ from those in the four standardised methods, this method is recommended.

Similarly, the roadmap suggests that stochastic processes are an appropriate approach to examining how different levels of “uncertainties”, or stochastic sources influence outcomes. This can be done by varying certain sources of probability while retaining others.

The research question in this study does not lie in the categories of the first four methods suggested by Davis (2007). In this study, buyers with their own selection strategies interact with suppliers in the market, and as a result, trust and reputation networks are progressively built along the simulation time steps. This approach corresponds to agent-based simulation modelling interaction between buyers and suppliers. In addition, transactional uncertainties, and the probability of supplier (opportunistic) behaviour is modelled with random variables, which correspond to a stochastic process. Therefore, this study integrates stochastic processes and agent-based simulation, which are customised to investigate the disproportional effectiveness of Information Accuracy and Transaction Volume on the performance of buyer firms in the long-term perspective.

Table 3-2 Comparison of Simulation Approaches (Davis et al, 2008)

Simulation Approach	**Focus**	**Common Research Questions(s)**	**Key Assumptions**	**Theoretical Logic**	**Common Experiments**
System Dynamics	Behaviour of a system with complex causality and timing	What condition create system instability?	• Systems of intersecting circular causal loops • Stocks that accumulate and dissipate over time • Flows that specify rates within system	• Description • Inputs to a system of interconnected causal loops, stocks, and flows produce system outcomes	• Add causal loops • Change mean of flow rates • Change variance of flow rates
NK fitness landscapes	Speed and effectiveness of adaptation of modular systems with tight versus loose coupling to an optimal point	• What is the performance of the optimal point? • How long does it take to find an optimal point (e.g., high-performing strategy)?	• System of N nodes, K coupling between nodes • Fitness landscape that maps performance of all combinations • Adaptation via incremental moves and long jumps • •	• Optimization • Adaptation of a modular system using search strategy (i.e., long jumps, incremental moves) to find an optimal point on a fitness landscape	• Vary N and K • Change adaptation moves • Add a "map" of the landscape • Create an environmental jolt
Genetic algorithms	Adaptation of a population of agents (e.g. organizational) via simple learning to an optimal agent form	• What affects the rate of adaptation (or learning or change)? • When and/or does an optimal from emerge?	• Population of agents with genes • Evolutionary adaptation • Variation via mutation(mistake) and crossover(recommendations) • Selection via fitness (performance) • Retention via copying selected agents	• Optimization • Adaptation of a population of agents using an evolutionary process toward an optimal agent form	• Vary mutation probability • Vary crossover probability • Vary length of time of evolution • Create an environmental jolt
Cellular automata	Emergence of macro patterns from micro interactions via spatial processes (e.g., competition, diffusion) in a population of agents	• How does the pattern emerge and change? • How fast does a pattern emerge?	• Population of spatially arrayed and semi-intelligent agents • Agents use rules (local and global) for interaction, some based on spatial processes. • Neighborhood of agents where local rules apply	• Description • Interactions among agents following rules produce macrolevel patterns	• Change the rules • Change the neighborhood size
Stochastic processes	Flexible approach to a wide variety of research questions, assumptions, and theoretical logics	• No specific research questions beyond asking what the effects of varying the stochastic sources are	• One of more processes by which system operates. • One or more stochastic sources (e.g., process elements) • Probabilistic distributions for each stochastic source	No specific theoretical logic	• Chang stochastic sources • Vary levels of stochasticity • Unpack constructs • Change pieces of theoretical logic

3.3.3 "Create Computational Representation"

For the development of Computational Representations, Davis (2007) suggests that three activities (1) operationalizing the theoretical constructs, (2) building the algorithms that reflect the theoretical logic of the focal theory, and (3) specifying assumptions that relate the theory and results. Though three activities are distinguished, activities are conducted interactively in the course of the representation because constructs, algorithms, and assumptions are highly interconnected.

Operationalising Theoretical Constructs

Definitions of computational measures are a key component of operationalizing theoretical constructs. The process of operationalization involves selecting the right computational measure for each construct and a range of values for each construct. In order to build reader intuition and confidence and to enhance the clarity of the theoretical contributions, it is also important to use construct definitions and names consistent with existing literature where possible.

Building Algorithms

As part of the computational representation, "algorithms" in software are also built to capture the logical flow of the simple theory adopted. Davis (2007) suggests that the algorithms should consist of a chain of adjusting steps for construct values in accordance with the simple theory. According to the roadmap, adjusting the tension between simplicity and accuracy is one of the most important issues in algorithm development. An algorithm's complexity should be determined by the complexity of the underlying theoretical logic as well as the popular trade-off between simplicity and accuracy. Similarly, simulation research attempts to focus on the core logic while eliminating the non-essential by balancing simplicity and accuracy in the computation models.

Specifying Assumptions

Some assumptions are directly related to boundary conditions of the theory while other assumptions are due to the simplification of the simulation itself, for example, a relative easiness of computer code, for the purpose of focusing on the central logic. Thus, these assumptions are closely related to the complexity of the computational models.

In Chapter 4, a simulation model is developed which includes theoretical logics, constructs, and assumptions. A B2B marketplace either of traditional or digital platform is modelled where coordinators build consortia to maximise their long-term profits in response to given outsourcing opportunities. Firstly, coordinators in this market are provided with ITO opportunities with the different levels of technological unpredictability and measurement difficulty. For partner-selection strategy, they take Trust or Reputational strategy. As suppliers, they behave cooperatively or opportunistically. Also, the winning consortium members gain their profits in accordance with the assessment result of a delivered IT service. Their decision-makings and profits are formulated through a pre-defined rewarding rule.

The following key constructs are operationalised to embody this simulation model.

- Buyer firms can feedback and access information on supplier's tendencies to behave cooperatively or opportunistically (Chakravarty et al., 2014).
- Buyers choose their suppliers based on two strategies: one that continues from past positive results and another based on the reputation gained within the network (Gopal and Koka, 2012; Poppo and Zenger, 2002).
- Suppliers can behave cooperatively or opportunistically for their interests of own sake (Goo et al., 2007).
- A supplier with a prior relationship can be acquired with lower searching and contracting costs than a new supplier (Goo *et al.*, 2007).
- When opportunism is detected, the supplier will subsequently experience a negative impact on acquiring future business opportunities (Zheng et al., 2019).
- Technological unpredictability and measurement difficulty exist together in ITO business environments (Goo *et al.*, 2007).

Next, the following measures are developed for the comparison between Trust and Reputation strategy.

- Average number of Ties (Ties)
- Average proportion of opportunistic partners (Opportunism)
- Average cost of partner acquisition (Acquisition Cost)
- Average cost of penalty paid for quality degradation (Penalty Cost)
- Average profitability of coordinator group (Profitability)

All the measures are scaled proportional (between 0 and 1) to the maximum value achievable by the given parameters setting.

Finally, the following key assumptions are made in this research.

- Buyer firms can feedback and access information on supplier's tendencies to behave cooperatively or opportunistically (Chakravarty et al., 2014).
- Buyers choose their suppliers based on two strategies: one that continues from past positive results and another based on the reputation gained within the network (Gopal and Koka, 2012; Poppo and Zenger, 2002).
- Suppliers can behave cooperatively or opportunistically for their interests of own sake (Goo et al., 2007).
- A supplier with a prior relationship can be acquired with lower searching and contracting costs than a new supplier (Goo et al., 2007).
- When opportunism is detected, the supplier will subsequently experience a negative impact on acquiring future business opportunities (Zheng et al., 2019).
- Technological unpredictability and measurement difficulty exist together in ITO business environments (Goo et al., 2007).

3.3.4 "Verify Computational Representation

Verifying the computational representation is an important step in developing theory using simulation methods. Verification involves tests of the accurate representation of central logic, internal validity, and level of confidence in interpreting the simulation results. Simulating data with the simple theory is the most important way researchers can verify their computational representation. The computational representation of central logic and its theoretical formulations are likely to be correct if the propositions are confirmed by the simulation outcomes. In addition, robustness test (or sensitivity analysis) can further verify their computational representation with an increased level of confidence. Tracking intermediate values of variables and testing with extreme values are also software techniques to further verify the computational representations.

Mismatches found in this verification process often help simulation researchers uncover errors in software coding, but sometimes reveal weaknesses in theoretical logic. These opportunities provide simulation researchers with new and unexpected theoretical insights.

In Chapter 5, a series of experiments are designed. Then, the basic test for verifying the developed simulation model is conducted assuming a traditional marketplace with the low level of Information Accuracy and the low level of Transaction Volume. The results at this experimental point are compared with the existing studies addressing the advantages of dyadic trust when marketplace is without digital platforms. This comparison confirms whether the model is consistent with extant theories. At the same time, the source codes are checked through tracking the values of key variables at each procedure of the model.

3.3.5 Experiment to Build Novel Theory

Experiments involve confirmation of known theory and further build new theories by revealing fresh relationships among constructs and novel theoretical logic, while verification of the computational representation attempts to demonstrate the accuracy of the computational representation. Simulation methods also offer the advantage of experimentation. Formal modelling experiments are restricted by mathematical tractability, whereas empirical experiments are restricted by data limitations. Contrary to this, simulation methods allow experimentation across a wide range of conditions by modifying the software code.

There are several factors that should be considered when designing experiments. The most important criterion is theoretical contribution. Understanding where theoretical contributions may be found usually starts with knowledge of the literature. It is possible to make serendipitous discoveries, but by knowing the literature, the researcher is often able to identify theoretical discrepancies and experiment where they can increase their chances of finding intriguing theoretical insights.

In Chapter 5, the complete tests for comparing the two types of partner-selection strategies are conducted following the experimental scenarios. Then, the analysis results reveal the conditional effectiveness of each type of strategy at the different levels of information accuracy and transaction volume.

3.3.6 Validate with Empirical Data

Validation of theories developed through simulation methods is a final step in theory development. In order to validate a simulation for a given empirical context, the simulation must match the empirical evidence. If it does so, the theory is validated for that particular empirical context. This strengthens its external validity.

New findings from simulation studies can be validated effectively in several ways. One approach is to compare simulation results with statistical results derived from large-scale empirical data, which can serve as a broad validation tool. Case study data can also be used to demonstrate that simulation results and theoretical logic are consistent with specific details of one or a few examples. Both approaches can be used, depending on data availability.

For this study, considerable empirical evidence supports the simple theories applied to this research (i.e. relational exchange theory, social capital theory, transaction cost theory and agency theory). Therefore, the new findings derived from the simulation results can attain a certain level of external validity.

3.4 Simulation studies in management studies

Simulation in management studies is employed as a methodology to develop theory rather than as a tool to solve a problem (Harrison et al., 2007). Social scientists use it to develop theories, which are more complex than predicting the future of a system. Simulations are used in this manner in contrast to engineering and operational research fields, which tend more to focus on prediction than theory development. In particular, the rapid increase in the use of simulation in recent years is thanks to agent-based simulation, through which the ability to discover non-linear relationships with variables that visualise a mechanism through which those observations could emerge (Gilbert and Terna, 2000).

Simulation method has also been considered as a sensible approach to model a marketplace (Albino *et al.*, 2007; Chang *et al.*, 2010). This is because a supply chain network is formed by interactions among economic actors–- whether it is buyer or supplier firms. As a consequence of individual interaction, each actor’s network position within either dyadic or network in terms of configuration and performance changes at firm- and market-level simultaneously.

According to Davis (2007), the computer-based approach creates “computational representations for constructs derived from existing literature, theoretical logics establishing relationships among them and assumptions defining research boundary conditions". Therefore, Simulations enable theories to be developed or extended using constructs, theoretical logic and assumptions that are necessary for a well-crafted theory (Harrison et al., 2007).

The simulation research methodology has gained recognition in the strategic management discipline as an important tool of scientific inquiry in addition to deductive theoretical modelling and inductive empirical analysis (Harrison *et al.*, 2007; Rivkin and Siggelkow, 2007). The simulation methodology has also recently been introduced in the IS discipline to tackle challenging problems driven by the increased complexity in the sociotechnical systems (Hahn and Lee, 2021; Haki *et al.*, 2020; J. Lee *et al.*, 2003; W. Oh *et al.*, 2016).

3.5 Summary

In spite of its usefulness, the simulation approach is rarely conducted in the studies of partner-selection strategy which relate to the research question of this study. Therefore, this chapter explained why and how a simulation approach was applied to this research, particularly following the roadmap of Davis et al (2007).

Firstly, the roles of a simulation approach in management studies were explained. It was shown that a theory developed or extended through a simulation approach could be qualified as a well-made theory. Next, this approach was compared with a deductive and inductive approach. This comparison provided a better understanding of the usefulness of a simulation approach. In addition to the comparison, several research settings were identified where this approach is applicable. Finally, this section illustrated the roles of a simulation approach in developing a new theory or extending an existing theory and the two evaluation criteria for a simulation study.

Secondly, it was described how this research proceeds based on "the roadmap for developing theories with simulations. The simulation steps to address the research question in this study include (1) beginning with a research question and simple theory, (2) choosing a simulation method, (3) creating computational representations, (4) verifying computation representations and (5) experimenting to build a novel theory. The final step of validating with empirical data was excluded.

In the next part, a simulation model is developed based on existing theories and empirical studies to compare Trust and Network Reputation at the different levels of information accuracy and transaction volume.

Chapter 4 Simulation Model

In Chapter 4, the simulation model of the supply chain network will be described in detail in this section, including the interactions between multiple suppliers and buyers. The computational model will outline the assumptions of the actors, inputs, outputs, and formulas used at each stage of the process, including the creation of business opportunities, bidding, execution, evaluation, and updating of market information. Finally, the parameters and measurements used in the simulation experiments will be presented, along with their definitions and formulas.

4.1 Simulation Procedure

The simulation model follows the sequence of procedures outlined in Figure 4-1. At the beginning of each round, business opportunities are presented to the market, and active coordinators get ready to form a consortium. Information necessary for each consortium is disseminated to the suppliers in the market via an RFP (Request for Proposal). During the bidding stage, when a supplier submits their bidding proposal to one or more consortia, the coordinator chooses the best supplier based on their partner selection strategy. This stage involves evaluating potential suppliers, negotiating terms and conditions, and signing the contract. Once all the suppliers for the required technologies have been secured, the consortium is successfully formed by the coordinator. In the implementation stage, opportunistic suppliers who were unknowingly included in the previous stage may try to further their own interests by investing fewer resources than promised in the contract. The coordinator endeavours to detect and monitor such opportunistic behaviour at this stage. In the final evaluation stage, the quality of the completed project is assessed. Based on the evaluation results, coordinators and suppliers are rewarded and the consortium is disbanded. Finally, the coordinator registers the feedback or rating information regarding each supplier's behaviour to the reputation management system.

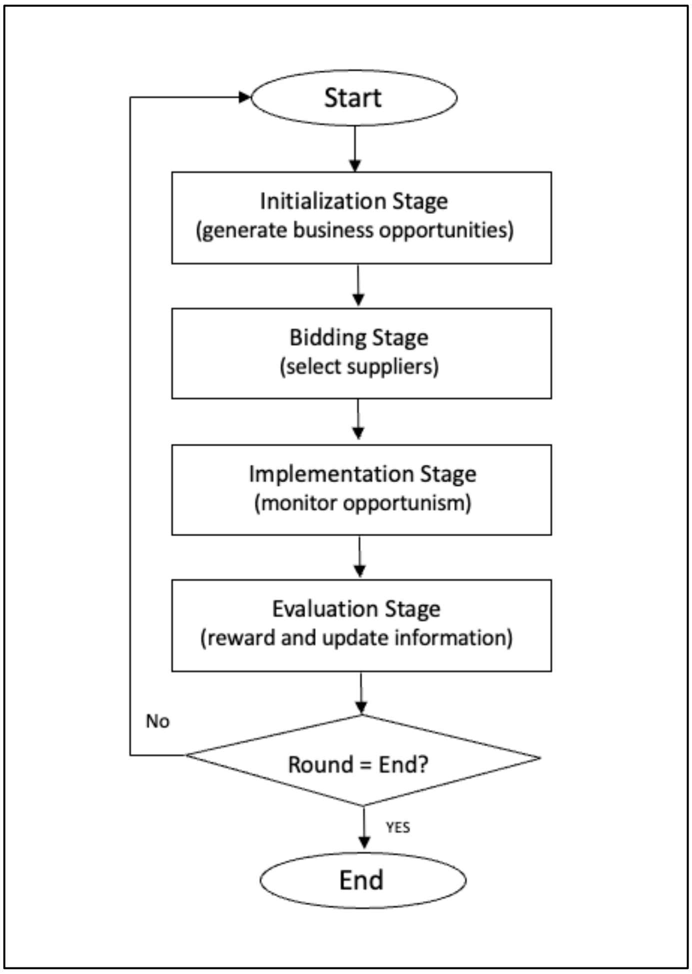


Figure 4-1 Simulation Procedure of Buyer-Supplier transactions

4.1.1 Business Opportunities in the Market – Initialization Stage

At the initial stage, business opportunities (BOs) are created within the market at regular intervals. These BOs are randomly assigned to buyers who possess coordination abilities, referred to as coordinators from here on. Each BO outlines the technical expertise required to complete an IT project and a reward model for the consortium members (coordinator and suppliers) based on the assessment of the project's quality.

This research is built on the following key assumptions for a model of the buyer (coordinator) and suppliers.

- A market participant can possess either coordination abilities (as a coordinator and buyer) or technical skills (as a supplier).

• The coordinator outsources or secures multiple suppliers on the marketplace and manages the project for its client, but it is not considered a participant or actor in this study.

• The coordinator adopts one of two strategies when selecting participants for the consortium. Out of a total of 100 coordinators, 50 use the relation-based selection strategy, while the other 50 use the reputation-based strategy. The outcomes of these two groups are compared and analysed.

• Suppliers are also divided into two groups of equal size, each with different behavioural strategies. Out of a total of 100 suppliers, 50 pursue profit maximization in cooperation with the coordinator through opportunistic behaviour, while the other 50 adopt cooperative behaviour. Please note that opportunistic suppliers are willing to accept penalties in pursuit of additional profits.

• Information Accuracy and Information Volume are assumed to be distinguishing variables between digital platforms and traditional marketplaces. In other words, it is generally assumed that digital platforms based on ICT tend to have higher values in these two aspects compared to traditional markets.

• The reward-related parameters used in the simulation, such as the transaction profit rate and loss compensation rate, were selected at levels typically applicable in regular business transactions, ranging from about 5% to 20% of the average transaction amount.

• The project consortium is assumed to comprise one coordinator and four suppliers with varying technical capabilities. In this setup, coordinators from two groups take turns selecting partners. If no supplier with the necessary technology is available, this situation may lead to the inability to form the project consortium for that specific round, potentially resulting in a loss of business opportunity for that period.

• The quality of the project is assumed to be assessed by a third-party organization. If opportunistic behaviour by a supplier is detected by coordinator, then the penalty is borne by the supplier. However, if such opportunism is not overlooked by the coordinator, this model assumes that the coordinator is responsible for the degradation in quality and, as a result, bears the losses associated with penalty expenses (for the client).

According to the above assumptions, a coordinator needs to build a consortium by selecting suppliers who have the required technical skills for the BO.

4.1.2 Buyer's supplier-selection strategy – Bidding Stage

During the bidding phase, technical suppliers present their bids to the consortium(s). The evaluation of potential suppliers, negotiating of terms and conditions, and the signing of contracts occur at this stage. Once all required suppliers are secured, the coordinator's consortium is established.

In this stage, suppliers who possess the necessary skills make their bids to the coordinator. It is assumed in this model that all business opportunities are open to all technology suppliers, either through traditional marketplaces or digital platforms, allowing any supplier to apply to multiple consortia within its resource capabilities. The coordinator of each consortium aims to select the best supplier from the candidates. To do this, the coordinator with a partner-selection strategy ranks the potential suppliers based on either their reputation or previous trust-based relationships and chooses the one with the highest score.

A collective penalty for opportunistic behaviour is also considered. For instance, opportunistic suppliers detected in previous rounds may be banned from bidding for a certain number of rounds. In the simulation model, a buyer evaluates the rankings of potential suppliers for j-th technology and invites the highest-ranked supplier into its consortium. For the k-th coordinator, the ranking of i-th supplier for the required technology of j-th is calculated using the model (Eq. 4-1).

$$Rank_{i,j}^{k} = W_{price} \times R_{price\ i,j}^{k} + W_{new} \times R_{new\ i,j}^{k} + W_{capital} \times R_{capital\ i,j}^{k} \qquad \text{(Eq. 4-1)}$$

In this simulation, the evaluation of suppliers by the coordinator is based on three factors: offered price, new supplier cost and social capital (reputation or trust). These factors are given equal weight and are represented by the symbols W_{price}, W_{new} , $W_{capital}$, respectively, with a value of '1'. The ranks of each of these factors of i-th supplier bidding for k-th buyer (coordinator) are denoted by $R^k_{price\ i,j}$, $R^k_{new\ i,j}$, $R^k_{capital\ i,j}$, respectively. The coordinator then chooses the supplier with the highest rank based on either their reputation or their dyadic trust, which is the main focus of this study. If the coordinator is unable to secure the necessary suppliers, the business opportunity is cancelled and the coordinator will not receive any rewards for that round.

Dyadic Trust

A coordinator who uses the Dyadic Trust-based supplier selection strategy values suppliers who have a previous positive working relationship. Dyadic Trust is a measure of the strength of the relationship between a coordinator and a supplier, based on the accumulated rewards that the supplier has contributed to the coordinator over a period of time. The stronger the relationship, the greater the trust. Coordinators using this strategy choose suppliers who have contributed the most rewards in the past. If a project is completed with high-quality output and without opportunistic behaviour from suppliers, the coordinator is rewarded in proportion to the contributions made by each technology supplier.

However, if opportunistic behaviour is detected, the defecting supplier is not rewarded and is banned from bidding for a certain period, making them less competitive in future opportunities with the same coordinators. If the channels for transmitting reputation information in the market are inefficient and not accurate about the quality of the supplier, it can be challenging for the coordinator to opt out the suppliers with opportunistic tendency, leading to negative impacts on the coordinator's performance or the performance of trust-based selection strategy.

Therefore, Dyadic Trust of the i-th supplier by the k-th coordinator is calculated during T-th round of the bidding stage can be calculated using Equation 4-2.

$$Dyadic\ Trust^k_i(t) = \sum_{t=1}^{T} Rwd^k_i \qquad \text{(Eq. 4-2)}$$

where Rwd_i^k is the promised reward (profit) from the i-th supplier to k-th coordinator at t-th round. *Rwd of a supplier* is zero (0) when the opportunistic behaviour is detected by coordinator.

Reputation

In other words, a coordinator that uses the reputation strategy in supplier selection looks at the evaluations from other coordinators instead of its own past experiences with the supplier. This means that the reputation of a supplier is a different factor compared to the mutual contribution calculated in Dyadic Trust. In this study, the reputation of a supplier is measured by the number of successful transactions it has had with other coordinators. Coordinators that use this strategy minimize the risk of supplier opportunism by choosing the supplier with the most positive recognition from other coordinators in the market.

In this study, Reputation of i-th supplier is calculated during t-th round of bidding stage:

$$Reputation_i(t) = \sum_{t=1}^{T} \sum_{i}^{All} Ties_i^k \qquad \text{(Eq. 4-3)}$$

where

$$Ties_i^k = \begin{cases} 1, & \text{when received a feedback from a coordinator} \\ 0, & when\ received\ a\ negative\ feedback\ (etected\ of\ its\ opportunism) \end{cases}$$

The distinction should be made between the actual reputation of a supplier, which is determined after the project is completed and based on feedback from buyers, and the reputation conveyed through market information channels.

The model considers the possibility of even opportunistic suppliers receiving positive feedback from coordinators and building a certain level of reputation if their opportunistic behaviour goes undetected during the consortium period. This scenario enables a comparison between the effectiveness of the two supplier selection strategies when it is difficult for coordinators to assess the quality of an ITO transaction outcome. Over time, as transactions occur repeatedly in the market, all suppliers accumulate two forms of social capital: dyadic trust and reputation from relationships with various customers. The supplier with the higher social capital score will be selected by the coordinator during the bidding stage.

4.1.3 Supplier opportunism and ITO uncertainty model – Implementation Stage

In the implementation stage, suppliers execute tasks using their technical skills, and the results are submitted to the coordinator who assesses the quality of the outcomes during this stage. In this study, it is assumed that opportunistic suppliers will contribute fewer resources to the consortium compared to the agreed amount, while coordinators monitor their behaviour in an effort to detect opportunism.

If the opportunism goes unnoticed, the opportunistic supplier uses the saved resources for other projects to earn additional profit. However, the buyer firms will be penalized for the quality loss caused by opportunistic behaviour during the execution period. In this model, suppliers who are caught engaging in opportunistic behaviour are penalized and are further restricted from bidding on new contracts for a certain period. This consequence of detected opportunism affects not only the short-term profits of the current round but also long-term growth. The relationship between supplier opportunism and buyer (or alliance) performance is an interesting topic, with evidence suggesting that opportunism has a negative impact on performance, including net revenue and relational duration (Goo and Nam, 2007; Parkhe, 1993).

<u>Environmental Uncertainty and Opportunism Model</u>

This study considers the uncertainties arising from the difficulty in measuring the quality of service provided by suppliers and the unpredictability of clients' technological requirements. Partner opportunism is cultivated largely by technology uncertainty and measurement difficulty (S. J. Carson *et al.*, 2006; Poppo and Zenger, 2002), and can be moderated by the social embeddedness, however, also its intensity or frequency can be determined by rewarding or risk actors face (Deeds and Hill, 1999).

In this model, the chances of a coordinator detecting opportunistic behaviour from a supplier depending on the difficulty of evaluating the ITO project tasks. If the technology used by the supplier cannot be easily assessed by other firms or the coordinator, it will be difficult for the coordinator to identify opportunistic behaviour from the supplier. This can result in a failure in quality control of the final project output, which can negatively impact the performance of the consortium and its profitability. Furthermore, rapid changes in technological requirements can also affect the performance of supplier selection strategies. For example, if only a few suppliers have the necessary technology and many projects require it, then even opportunistic suppliers are more likely to participate in the project.

The Uncertainty models applied in this study are summarised in Table 4-2.

Table 4-1 Comparison of two ITO Uncertainties: MD and TU

	Measurement Difficulty	Technical Unpredictability
Definition	The degree of difficulty or ambiguity in measuring performance of exchange partners	The degree of unpredictability or volatility of future states regarding IS requirements, emerging technologies, and/or environmental factors
Effect	Higher MD makes difficult to detect the defection	Keep demanding new partners for more diverse technologies
Model	Tend to increase the number of ‘opportunistic’ suppliers	Tend to increase the necessity of ‘new’ suppliers

4.1.4 Rewarding and Update of Supplier Information–- Evaluation Stage

At the end of an ITO transaction, the distribution of rewards for both the coordinator and suppliers is determined based on a reward rule. Suppliers who have acted cooperatively will receive a certain portion of the resources allocated as outlined in the contract. However, if the coordinator detects any opportunistic behaviour from a supplier, the supplier will not receive the full reward amount as stated in the agreement. If the project is completed successfully and meets the quality standards outlined in the contract, the coordinator will give positive feedback to the participating suppliers and share this information in the market, which will be used by other coordinators as a factor in choosing suppliers in future bidding rounds. Similarly, suppliers who have successfully completed a project will receive positive evaluation, which will be shared in the market and used as consideration for selection in future bids.

In this study's simulation model, the rewards received by coordinators and suppliers are based on whether the opportunistic behaviour has been detected or unnoticed. Opportunistic suppliers seek extra profits, *Px*, on top of the promised reward, *RwdP,* by attempting to save the required resources. In case of that the coordinator fails to detect this defection, the resulting reward will be reduced by *Px* from the original reward, that is, *RwdC – Px*. Then, for the coordinator, *Px* is considered as a penalty cost for failing its duty to guarantee the contracted quality. Alternatively, when an opportunistic behaviour of a supplier is detected by a coordinator, a supplier pays a penalty (or loses a portion of profit) and received a decreased reward of *RwdP-Px.* A Reward rule applied in this simulation model is summarized in Table 4-2.

Table 4-2 Reward rule for the detected and undetected cases

	Coordinator(buyer)	Opportunistic Supplier
Undetected	*RwdC – Px*	*RwdP + Px*
Detected	*RwdC*	*RwdP - Px*

Finally, the coordinators report their evaluation of the supplier's behaviours at the end of the project. his information about whether a supplier is opportunistic or cooperative is shared through the market's reputation system. In traditional markets, this information is usually spread through a network of buyers' direct and indirect connections. However, in B2B digital platforms, the information, including feedback about the supplier's behaviour, is stored, managed, and easily accessible through an IT-based centralised system created by the platform.

4.2 Model of attributes of B2B digital platforms

The study views information accuracy and transaction volume as the key differences between B2B digital platforms and traditional marketplaces (Gefen and Carmel, 2008; Van Alstyne and Parker, 2016; Zhou et al., 2022).

4.2.1 Information Accuracy

The study posits that the differences in information transmission channels between traditional marketplaces and B2B digital platforms can affect the quality of information regarding supplier reputation. B2B digital platforms, with their centralised IT systems, offer a more transparent and efficient channel for transmitting information about supplier behaviour, whereas traditional marketplaces may lack this level of transparency, leading to a potential overstatement or underestimation of a supplier's actual reputation. This can put coordinators at risk of relying on inaccurate information and result in them being unable to select the best available partners in the market due to the limitations in the flow of information.

This study quantifies the impact of the structure of information channels on the accuracy of information regarding supplier reputation. It looks at how buyers face challenges in determining the actual reputation of partners and their past opportunistic behaviour, due to the inefficiencies in the information flow. This inefficiency can cause ambiguity for buyers, leading to an overestimation or underestimation of a supplier's actual reputation.

Firstly, the delivered reputation of i-th supplier at t-th round (time) can be formalised as Eq. 4-4.

$$Reputation_i(\mathrm{t}) = \left(1 + \frac{1}{IA}\right) \cdot Actual\ Reputation_i(\mathrm{t}) \qquad \text{(Eq. 4-4)}$$

where IA is a random variable representing the degree of information accuracy in a marketplace. The smaller the mean value, the greater the unreliability of the delivered reputation compared to its actual value, resulting in uncertainty in supplier selection. On the other hand, a larger mean value conveys a closer representation of the actual reputation to the coordinator. In an efficiently functioning market, the volatility value is small, and the buyer receives reputation information that is closer to the actual value. The Actual Reputation represents the ideal, realistic value where the information recorded by the customer is transmitted without any alterations. Generally, platforms are considered to have a higher efficiency and accuracy of information delivery compared to traditional markets due to their systematic approach to information creation, processing, and delivery.

4.2.2 Transaction Volume

In this study, transaction volume is closely related to the quantity of information in B2B digital platforms, modelled as the number of business opportunities available in the market. The increase in transactions resulting from advancements in technology, such as software development outsourcing and globalization, distinguishes these platforms from traditional marketplaces, which have relatively less frequent transactions and smaller number of suppliers.

In the simulation model, transaction volume (TV) is modelled based on the number of business opportunities (or consortia) generated in each round. This model allows the researcher to analyse an impact of B2B digital platforms on the performance of supplier-selection strategies. The more opportunities that arise, the more frequent the interactions become and the more information about supplier behaviour is generated, shared, and accumulated over time.

4.3 Parameters and Measures

4.3.1 Parameters (Inputs)

The objective of the experimental design is to examine the impact of uncertainties resulting from the shift from traditional marketplaces to B2B digital platforms on the performance of coordinators who employ two different strategies. The input parameters in this study, such as uncertainty, information accuracy, and transaction volume, represent ITO transactions and affect the configuration of the supplier network and costs based on the chosen supplier selection strategy.

A full factorial design is conducted using the combinations of Information Accuracy (IA), Transaction Volume (TV), Technological Unpredictability (TU), and Measurement Difficulty (MD) as experiment scenarios. The experiments control for the parameters as listed in Table 4-3. Each parameter is set at three different levels: low, medium, and high. The supply chain network is characterized by one combination at a time.

Table 4-3 Simulation Parameters

Parameters	Concept	Value (setting)
Information Accuracy (IA)	Level of informational correctness in the information of a supplier's reputation when delivered to a coordinator.	{0.1, 0.5, 0.9}

Transactional Volume (TV)	Level of information volume traded in the market. Number of Active Business Opportunities at each simulation round.	{8,12,16}
Measurement Difficulty (MD)	MD is defined inversely to Detectability in range of {0.75,0.5,0.25}, High level of Detectability (0.75) represents Low level of MD. And Low value of Detectability represents a high level of MD.	{0.75,0.5,0.25} of Detectability represents Low, Mid and High level of MD respectively.
Technological Unpredictability (TU)	Number of technological skills required at a marketplace. The more types of technology demand in the market, the more difficult it becomes for a company to predict which technologies will be needed.	{10,20,30}

4.3.2 Measures (Outputs)

The primary objective of the experiment is to analyse the impact of the partner selection strategy on the supplier network of each buyer group and to assess how the network structure affects the cost performance of the buyer firms. The following measures are key indicators of the network configuration and cost performance of the two buyer groups.

"Ties" refers to the average number of unique suppliers a coordinator has worked with in a round, based on either the Reputation or Trust strategy. This metric demonstrates how each strategic group engages with a diverse set of suppliers under similar circumstances.

Coordinators who choose suppliers based on Dyadic Trust tend to maintain relationships with existing suppliers, assuming that past positive experiences will continue in the future. Meanwhile, coordinators who prioritize reputation-based partner selection will opt for suppliers with established reputations, as evaluated by other coordinators. As new business opportunities arise and new skills are required, both strategic groups will gradually increase the number of suppliers they engage with over time. However, the difference in the scale of supplier experiences will depend on whether the coordinator selects a supplier based on past trust or market evaluation. The unit of measurement for "Ties" is the number of suppliers.

"Acquisition Cost" refers to the average cost incurred by each strategic group during the process of searching, evaluating, and negotiating contractual terms with suppliers.

For example, the acquisition cost of i-th supplier for k-th buyer is the summation of the following equation (Eq. 4-5).

$$AccCost_i^k = \begin{cases} AccCost_{old}, & \text{when supplier is an existing supplier of buyer} \\ AccCost_{new}, & \text{when or new supplier} \end{cases}$$

(Eq. 4-5)

Typically, the acquisition cost of a new supplier is higher compared to an established supplier with a history of contracting and collaboration. Hence, the simulation experiments are set up with the condition that $AccCost_{new} > AccCost_{old}$.

Working with an existing supplier who has a proven track record can help a buyer save on acquisition costs, as they won't have to spend time and resources searching, evaluating, and negotiating with a new partner. The unit of measurement for "acquisition cost" is monetary and can be influenced by the number of partners that each strategy, referred to as “Ties”, has experience working with at a given time.

"Opportunism" is a metric used to assess how efficiently buyers with different selection strategies are able to detect opportunistic suppliers and eliminate them from the consortium selection process. The level of opportunism can be calculated as Eq. 4-6.

$$Opportunism^k(t) = \frac{\sum Opportunistic\ supplier_i^k(t)}{\sum Cooperative\ supplier_i^k(tO + \sum Opportunistic\ supplier_i^k}$$

(Eq. 4-6)

where, $\sum\ supplier_i^k(t)$ is equal to ‘1’ if a supplier participates in the consortium lead by k-th coordinator, and ‘0’ if not included in the consortium.

As the simulation rounds progress, the number of transactions between the buyer and supplier increases, and buyers accumulate information (reputation) about the supplier's behaviour. This study compares and analyses the proportion of opportunistic suppliers and their changes over the simulation period. As the rounds advance, the coordinator's supplier selection strategies work to prevent the selection of opportunistic suppliers through their experiences with the supplier or information about their past behaviour shared on the network. The supplier selection strategy mechanism enables buyers to become better at identifying opportunistic suppliers over time, leading to a decrease in the percentage of opportunistic suppliers. In this study, the average value of the last 10 rounds of simulation is analysed to exclude outliers. (Unit: percentage, %).

"Penalty cost" at the t-th round is the average cost paid by each coordinator for the failed detection of opportunistic suppliers (monetary unit).

A high proportion of opportunistic partners can lead to significant project management costs and a higher risk of quality degradation. In this study, when the coordinator fails to identify an opportunistic supplier in the consortium, the responsibility for the quality degradation is modelled to affect the coordinator's long-term performance, resulting in an increase in penalty cost (monetary unit).

This model analyses two costs that result from a buyer's choice of partner. Firstly, "acquisition cost" is the cost the buyer must incur in finding a partner and negotiating contract terms. If the buyer chooses a partner who has worked with them before, this cost is lower compared to finding a new partner and negotiating again. This cost can be further reduced through repetitive work norms, which can reduce the monitoring cost of established partners during the execution period. Secondly, "penalty cost" for the buyer is a loss incurred due to the opportunistic behaviour of the selected partner. If the selected partner completes the contract as agreed upon, there will be no additional cost. However, if the partner acts in their own self-interest and causes defects, the coordinator (or customer) will incur additional costs for the project outcome, such as quality penalty costs. This penalty cost can be avoided if the buyer selects a cooperative partner or if the buyer's monitoring activities detect and prevent any opportunistic behaviour. Table 4-4 summarizes the costs in this study.

"Profitability" is the average accumulated profit of a coordinator for each strategy group at the end of the simulation period. It provides a comprehensive measure of the coordinator's performance for each selection strategy. By comparing the performance of the two groups, this study is able to analyse the impact of the selection strategy on the buyer's supplier network, cost changes, and the mechanisms that affect performance.

Table 4-4 Transactional costs associated with partner-selection strategy.

Category	Definition	Cost (Model)
Acquisition	Searching for new candidate suppliers for the projects. Negotiating and contracting cost	New Partner > Old Partner
Penalty	Extra cost of a buyer when a partner opportunism goes undetected, and quality degraded as a result. When detected, no penalty applied	Occurs when Opportunistic behaviour was not detected by coordinator

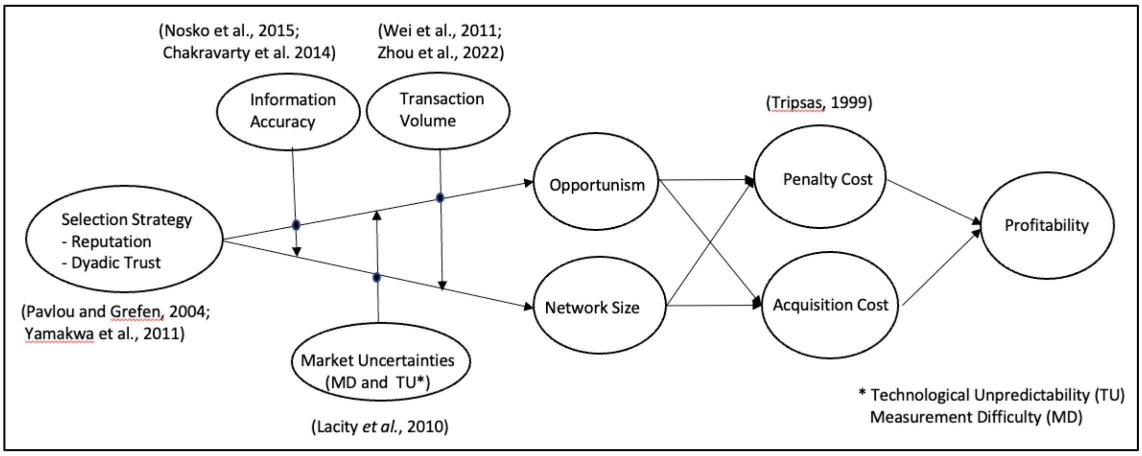


Figure 4-2 Simulation Model

Normalization of the measurement

For comparative analysis of different simulation scenarios, the measured values were normalized to relative levels in percentage (0-100%) based on the maximum attainable value. It should be noted that normalization was not necessary for opportunism, as it is a proportionally measured value.

The Conceptual Model implemented and analysed in this study is summarized in Figure 4-2.

4.4 Summary

The simulation model of ITO partner-selection strategy in a buyer-supplier network is illustrated along a 4-stage model. The technical description for ITO consortium, buyer's strategy of supplier-selection, supplier opportunism and rewarding scheme were represented this part. Finally, the parameters and measures are presented in detail to compare performance of Reputation and Dyadic Trust mechanism on simulated marketplaces. In next part, we address the central research question by experimenting with the selected parameters of the basic model.

Chapter 5 Experiments and Results

Chapter 5 presents a numerical and graphical analysis of the results obtained from the simulation. Firstly, the base model is validated by comparing the simulation results with the empirical findings from previous literature. Then, the two key attributes of B2B digital platforms, Information Accuracy and Transaction Volume are analysed to explain the preference for reputation-based supplier selection over trust-based selection.

The impact of ITO uncertainties, Technological Uncertainty and Measurement Difficulty on the performance of partner-selection strategies is also evaluated. The use of simulation experiments is an effective approach to solving complex market problems, as it allows for a wide range of analyses to be performed under different settings (as mentioned in the study by (Chang et al., 2010). The simulation model described in Chapter 4 was implemented using MATLAB R2022.

5.1 Experiment Design

A full factorial design of experiments is employed in this research to ensure efficient simulation tests and systematic analysis (Jiju, 2014). In this type of experimental design, each factor has discrete possible values, known as levels. An experimental point is a combination of these levels. All possible experimental points are tested in a full factorial design, making it useful for examining the interaction effects of multiple factors on outcomes. The design is widely used in research, especially when it includes factors at two levels, as its results are often used as a basis for more detailed studies (Jiju, 2014).

The following experiments are designed with the aim of solving the research questions outlined in Chapter 1.

Firstly, the base model is tested against empirical findings and theoretical propositions. It is assumed that the accuracy of reputational information for a new supplier is relatively low due to an inefficient information distribution (Bolton et al., 2004; Chang et al., 2010). Additionally, it is assumed that the transaction volume for the business will be smaller compared to an online platform that is unrestricted by region and time (as indicated in the "Experiment Validation" section of Table 5-1). The validity of the developed computational model is confirmed through the implementation of the base model test, where all experiment variables are fixed at a low level. A set of other parameters are carefully chosen to produce results that align with existing studies that support a supplier-selection strategy based on dyadic trust with a cost advantage from continuing the relationship when the market is low with uncertainties (the "Experiment of Base Model" section).

Secondly, the study investigates the impact of changing the variables representing the difference between the digital platform and traditional market (Information Accuracy and Transaction Volume) on the selection strategy. The experiments are designed to answer the main questions of the study (Experiments 2 and 3). The results from these experiments allow for the evaluation of the relative performance of the two strategies in different market settings.

Finally, the study further explores the effects of ITO uncertainties on the relationship between the market factors (Information Accuracy and Transaction Volume) and the supplier-selection strategies (Reputation and Trust) through additional experiments (Experiments 4 and 5).

These experimental settings are summarised in Table 5-1 to reflect the key factors that impact the market and transaction characteristics experienced by ITO consortia in both B2B digital platforms and traditional marketplaces.

Table 5-1 Design of Simulation Experiments

Experiment	Variable	Information Accuracy	Transaction Volume	Technological Unpredictability	Measurement Difficulty
Base Model	-	L	L	L	L
1	IA	L, M, H	L	L	L
2	TV	L	L, M, H	L	L
	IA x TV	L, H	L, H	L	L
4	TU	L, H	L, H	L, H	L
5	MD	L, H	L, H	L, H	L, H

Level: L (Low), M(Mid) H (High)

An 'Experiment' represents a scenario in the simulation, with each scenario designed to observe the impact of specific variables. For instance, Experiment 1 analyses the effect of the IA variable by varying it across three levels: Low (L), Medium (M), and High (H), while keeping all other variables at a low level (L) to eliminate their influence.

Experiment 2 investigates the impact of the TV variable while keeping the other variables at low levels. Experiment 3 involves a combined analysis of the IA variable's impact alongside other factors. Experiments 4 and 5 focus on analysing the effects of TU and MD by only considering Low (L) and High (H) levels, respectively, and also explore the overlapping effects based on combinations of IA and TV levels.

Each experiment was conducted over a range of 1 to 200 rounds and the results were averaged over 100 repetitions to minimise the impact of outliers.

5.2 Validation of the Base Model

In the first part of the experiment, the researcher compares the simulation results of the base model with empirical findings and validates the proposed model.

To analyse the test results, this study measures various parameters such as (a) the level of opportunism, (b) the penalty (loss) due to undetected opportunism, (c) network size (ties), (d) the cost of acquiring new partners, and (e) the accumulated profit at the end of the simulation period. The base model is restrictive in that the two key parameters, the accuracy of information about a supplier and the volume of transactions in the marketplaces, are both set low. In this experiment, the level of uncertainties of TU and MD are fixed at a low level to minimize external impacts. In subsequent experiments, these parameters are varied to show their impact on the performance of the partner-selection strategy and under what conditions firms with a reputation strategy outperform firms with a trust strategy.

Figure 5-1 shows the growth of the average number of related suppliers for two coordinator groups with reputation- and trust-based supplier selection strategies. The measurement is normalized in percentage against the maximal level of network expansion; 100% indicates that a coordinator has worked with all available suppliers in the marketplace. The Reputation coordinator group (in blue) averages ties with around 23.5% of all suppliers at the end of the simulation period, while the Trust coordinator group prefers to repeat relationships once a supplier is recognised as trustworthy and the number of ties with new suppliers is around 16%, which is 8% lower than the Reputation strategy.

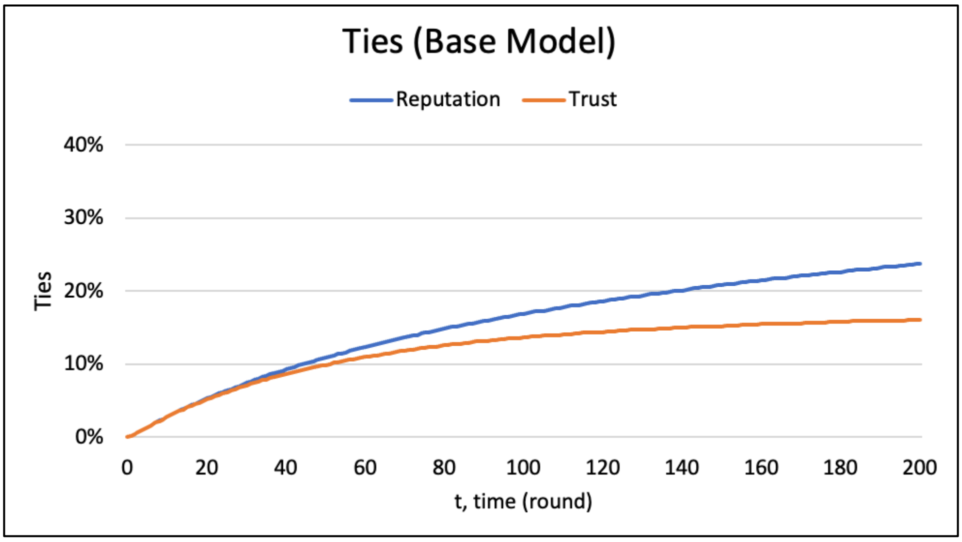


Figure 5-1 Result of Base Model Test: Ties

Figure 5-2 illustrates how the cost of acquiring suppliers changes as a network of trust and reputation are gradually established as a result of interactions between suppliers and buyers over the simulation period. The results of the experiment indicate that the trust-based strategy reduces the acquisition cost paid to new consortium by repeatedly utilizing the network formed after a certain round of the simulation period (at around t=100 in Figure 5-2).

A high level of ties for the reputation strategy means that coordinators encounter more new suppliers for the same number of projects and have to pay more acquisition costs for searching, evaluating, and negotiating with new suppliers. In this simulation result, a larger network contributes to the additional cost and then negatively impacts profitability. Higher acquisition costs for a reputation-based group are supported by empirical findings from Deeds and Hill (1999) and DiMaggio and Louch (1998) and ITO studies (Kim and Chung, 2003; J. N. Lee and Kim, 2005).

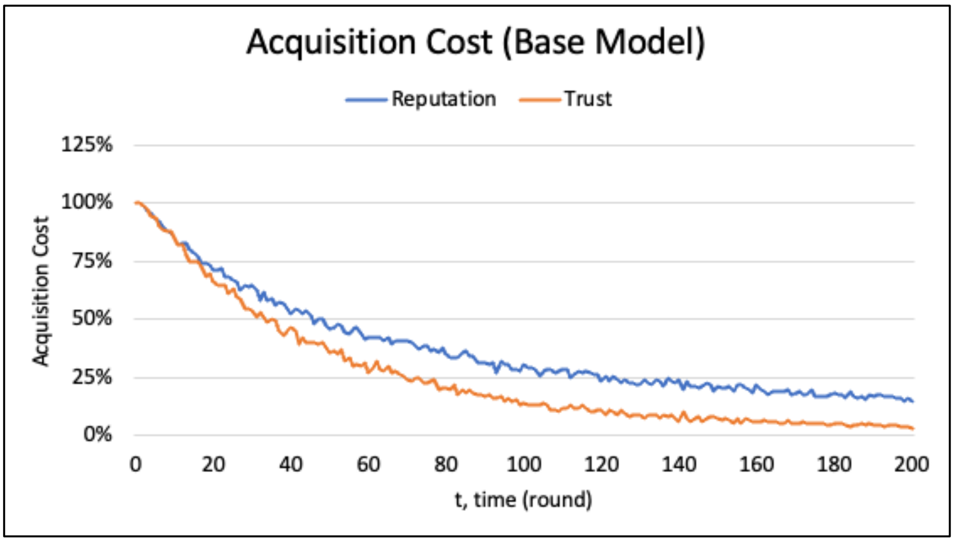


Figure 5-2 Result of Base Model Test: Acquisition Cost

Acquisition cost plays a key role in marketing studies as a part of the switching cost to enhance customer loyalty and prevent competitors from entering the market (Hess and Ricart, 2003). Although the strategic importance of these switching costs has become more important in today's increasingly connected supply chains (Hess and Ricart, 2003), few studies examined the cost as a performance index (F. R. Lin *et al.*, 2005).

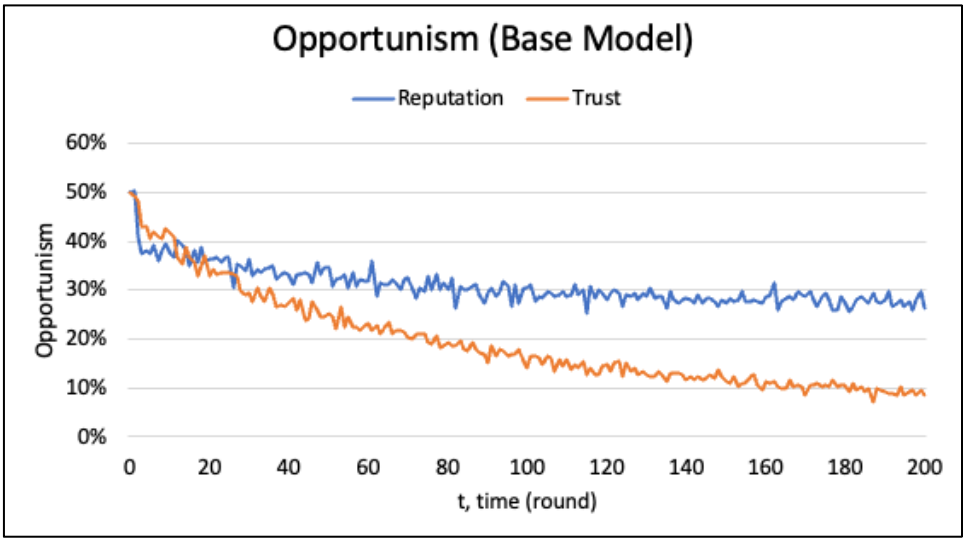


Figure 5-3 Result of Base Model Test: Opportunism

Figure 5-3 illustrates how effectively the coordinators control the admission of opportunistic suppliers into their consortia based on the two selection strategies over the course of the simulation period. The group of buyers using the Trust-based strategy appears to be better able to avoid opportunistic suppliers by using trustworthy suppliers found in the early rounds, responding to the slow and stable pace of change in technological requirements. On the other hand, as more suppliers are evaluated and shared by the buyers, reputable suppliers become well-known among coordinators in the marketplace. When a sufficient number of such reputable suppliers are identified, the number of opportunistic suppliers participating in the project decreases.

In the base model, the simulation results show that the trust-based strategy demonstrates a lower level of supplier opportunism (10.5%) and appears to be more effective in suppressing opportunism compared to the reputation-based exploratory strategy showing a relatively higher level of opportunism of about 27.5%.

Figure 5-4 compares the penalty costs of two buyer groups over a long-term series of projects. It can be observed that the trust-based strategy results in lower penalty costs and the result is proportional to the level of opportunism. An increase in the number of opportunists in the consortium leads to a higher chance of poor project quality, which results in a higher payment of penalty fees by the coordinator for failing quality control.

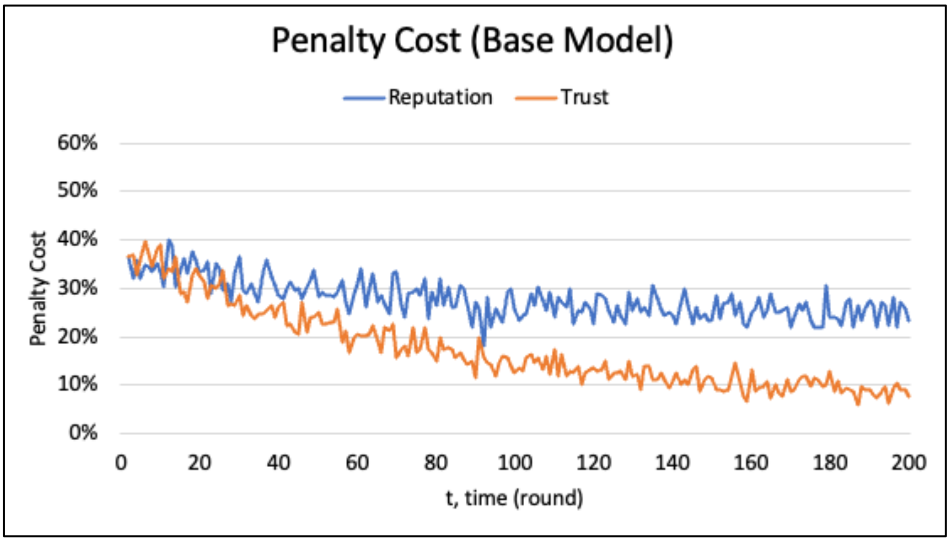


Figure 5-4 Result of Base Model Test: Penalty Cost

Finally, the overall performance of the two strategies is expressed as profitability, as shown in Figure 5-5. The cumulative profits of the Trust and Reputation-based groups are based on the analysis of project revenue, the acquisition cost of new partners, and the penalties paid by coordinators for deteriorated quality due to undetected defection. The results suggest that the profitability of the Reputation-based strategy is relatively low compared to the Trust strategy, indicating that in a market where the change of technological demand remained stable, the additional acquisition costs incurred to find a new supplier do not yield a sufficient reward. In Figure 5-5, the growth of the two strategy groups begins to diverge after around the 40th round, when coordinators with the Trust-based strategy have secured enough suppliers to meet their slowly changing technology requirements. As a result, the final profitability of the Trust-based strategy group is about 10% higher than that of the Reputation-based strategy group in the long term. Table 5-2 summarises the simulation results of the Base model test, expressed as a value normalized to the maximum value and averaged over the last 10 rounds.

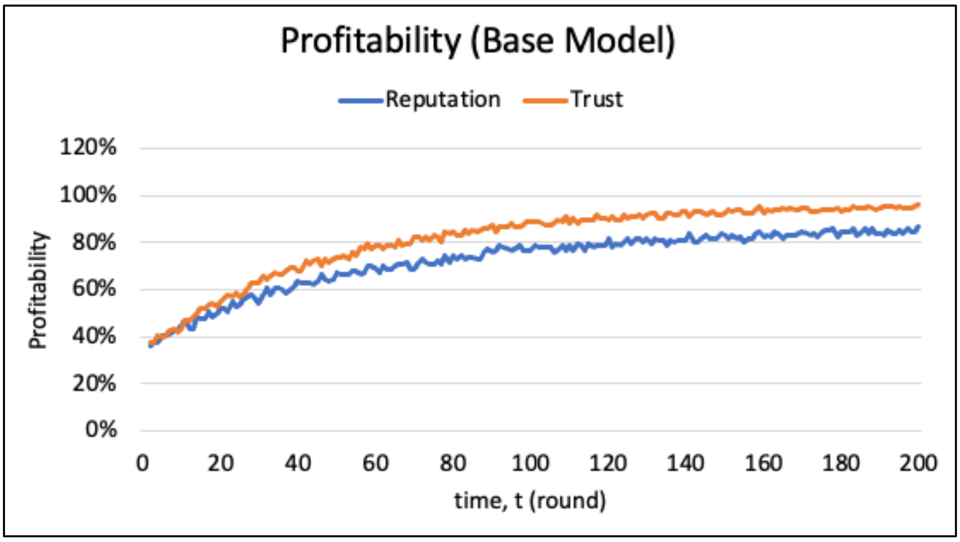


Figure 5-5 Result of Base Model Test: Profitability

Table 5-2 Simulation results of Base Model Test

Strategy	Reputation	Trust
Ties	23.5%	16.0%
Acquisition Cost	16.4%	4.1%
Opportunism	27.6%	9.0%
Penalty Cost	25.1%	8.6%
Profitability	84.8%	95.2%

According to the simulation results of the base model test, the Trust-based strategy of maintaining relationships with existing suppliers appears to be more favourable, as it is more effective in avoiding opportunistic suppliers and acquiring new suppliers in a market that does not require rapidly changing technologies and when the coordinator has knowledge of the sourced technology (Low MD). These results are in line with the findings of relational theory and ITO studies.

In the perspective of relational theory, the main outcome of positive interactions is an accumulation of goodwill and trust (Granovetter, 1992; Son et al., 2016), and mutual trust and commitment would serve to uphold agreed norms of collaboration reducing partner opportunism (Granovetter, 1992; Perry et al., 2004). positive interactions in the past would increase parties' expectations of the continuity of their relationship and it reduces partner opportunism since it encourages the relationship to look at the long-term return (Poppo and Zenger, 2002). In ITO studies, empirical findings in the ITO studies suggest that the performance of ITO alliances is improved by repeated relations, the longer duration of ITO contracts and the expectation of future opportunity (Goo *et al.*, 2007b; Goo and Nam, 2007; Kim and Chung, 2003; Poppo and Zenger, 2002).

5.3 Effect of Information Accuracy (Experiment 1)

This study attempts to analyse the role of Information Accuracy and Transaction Volume on the performance of supplier-selection strategy in order to answer the question of how reputation has become the dominant mechanism over dyadic trust in B2B digital platforms. In this experiment, the two key distinguishing attributes of B2B digital platforms from traditional marketplaces, Information Accuracy (IA) and Transaction Volume (TV) are varied from the low level to the high level, while other parameters remain the same as the values of the base model test.

5.3.1 Network size (Ties) and Acquisition Cost

Figure 5-6 demonstrates how the network ties of two coordinator groups are impacted as the level of information accuracy increases from a low to high level. The number of ties for coordinators who use the Reputation-based strategy (represented by blue lines) experiences a significant drop from 23.5 to 19.2 when the level of Information Accuracy increases from low to high. Conversely, the number of ties for coordinators who use the

Trust-based strategy remains steady at around 16 (represented by red lines) with little variation over the simulation period. Figure 5.7 highlights the long-term effects of changes in information accuracy on the performance of both strategies. The values shown are the final results after the simulation period has ended.

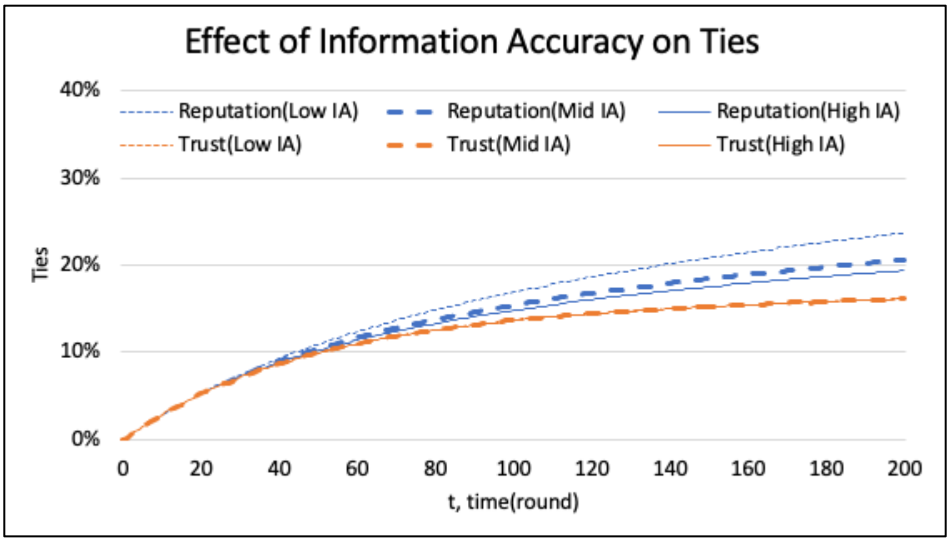


Figure 5-6 Simulation Results: Network Ties by Information Accuracy

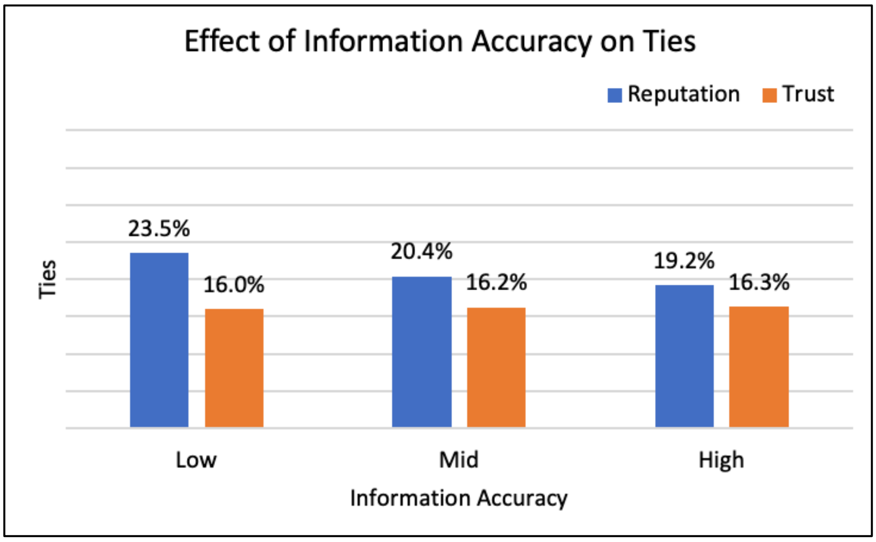


Figure 5-7 Simulation Results: Network Ties by Information Accuracy

The findings indicate that the average number of suppliers (Ties) required by a coordinator is influenced by the level of Information Accuracy. When information about suppliers in the market becomes more accurate, coordinators can detect opportunistic suppliers and minimise their admission into the consortium. On the other hand, if the accuracy of information about suppliers decreases, the coordinator's strategy for selecting suppliers may not effectively filter out opportunistic suppliers, leading to less successful outcomes.

Over time, coordinators come into contact with new suppliers and gain more information about their reputation in the market. As a result, after a certain point, the market will have established a sufficient pool of reputational suppliers to meet the demand from coordinators who follow the Reputation-based strategy. From then on, the growth of network ties slows down. In other words, with more accurate information about suppliers' reputation, coordinators are able to access a pool of trustworthy suppliers at an earlier time, rather than having to try more unknown suppliers to find reliable suppliers for the changing market demand.

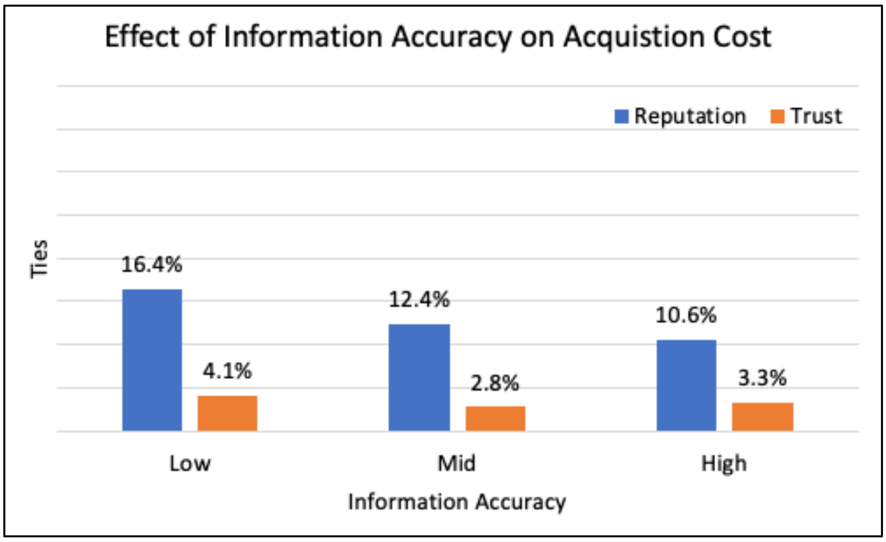


Figure 5-8 Simulation Results: Acquisition Cost by Information Accuracy

The optimal exploration of new partners, facilitated by the high level of Informational Accuracy, results in a reduction in costs associated with searching for and contracting with new suppliers (as shown in Figure 5-8). The simulation results highlight the impact of Informational Accuracy on the quantitative changes in B2B network configurations and the performance of alliances.

5.3.2 Opportunism control and Penalty cost

Figure 5-9 displays the impact of increasing information accuracy on the level of opportunism among two coordinator groups. As the accuracy of information rises from low to high, the proportion of opportunistic suppliers in the Reputation-based strategy (represented by blue lines) drops significantly from 27.6% to 18.6%. On the other hand, the level of opportunism for the Trust-based strategy (represented by red lines) remains unchanged at around 9%. Over the simulation period, the difference between the two lines remains minimal. Figure 5-10 shows the final values of the simulation results for the level of opportunistic suppliers among the two groups that employ different strategies.

The simulation results show that coordinators with the Reputation-based strategy experience a significant decrease in the level of opportunism from 27.6% to 18.6% as the accuracy of information increases. However, coordinators with the Trust-based strategy see a slight increase in opportunism from 9% to 9.4%. Figure 5-10 highlights the long-term effect of changes in information accuracy on the performance of the two strategies. The values are the final values at the end of the simulation period.

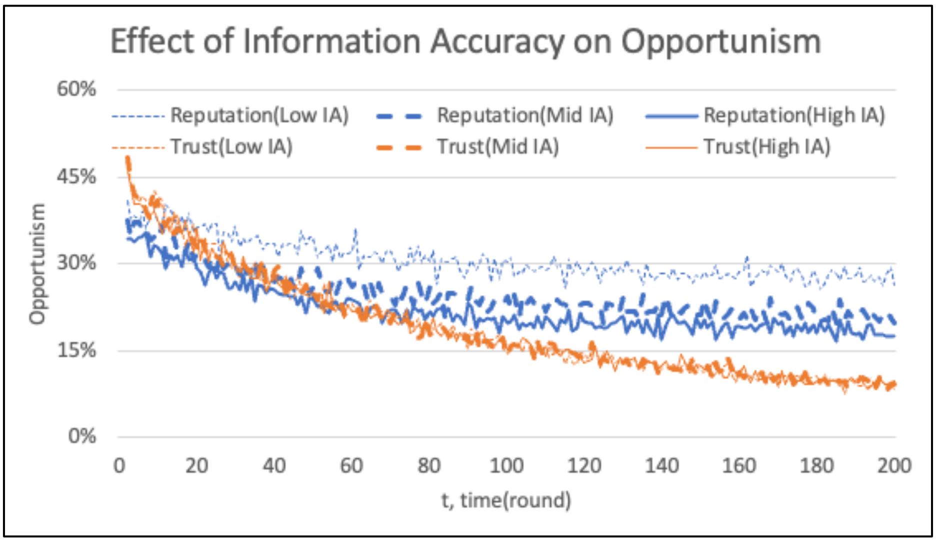


Figure 5-9 Simulation Results: Opportunism by Information Accuracy

The average level of Opportunism for Reputational strategy is higher than that of Trust-based strategy by 10.7%p when the accuracy of reputational information is not accurate. However, the gap between the two strategies quickly narrows to 2.2%p difference when information accuracy increases.

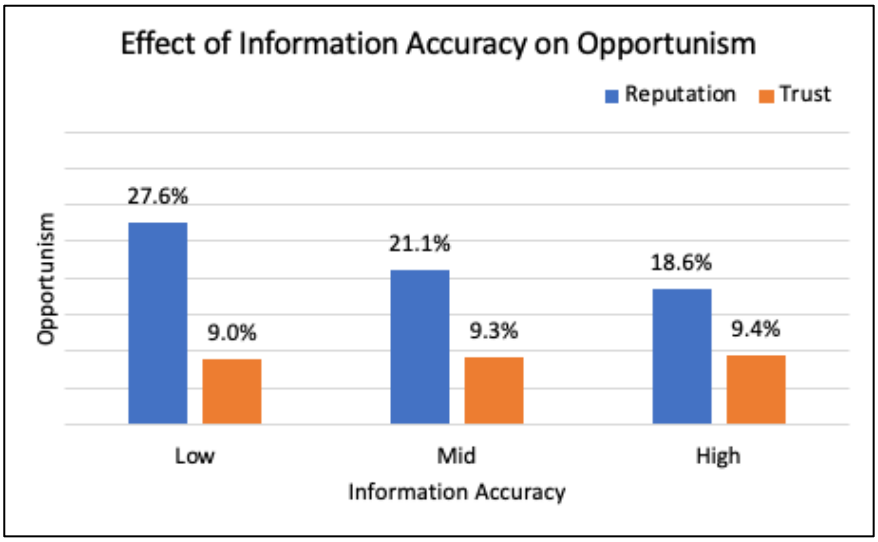


Figure 5-10 Simulation Results: Opportunism by Information Accuracy

As a Trust strategy prefer to continue with suppliers who have their own direct experiences, their choice of supplier does not depend on the information provided by third parties after forming a certain size of partner pool. This implies that the quality of the information provided indirectly by third-party participants has limited influence on the performance of a trust-based selection strategy.

On the other hand, a reputation-based supplier selection strategy is based on information about the supplier's reputation, which is evaluated collectively by other market participants. The accuracy of this information may vary, depending on the efficiency of the information transmission channel, whether it be in traditional markets or in more sophisticated digital platforms. Simulation results suggest that the trust mechanism is more effective in controlling opportunism in market environments where the information channel is inefficient, and the information delivered is inaccurate.

In an IT-enabled marketplace, coordinators are more likely to receive accurate information about a supplier's reputation, as it is recorded by previous coordinators who have worked with the supplier without loss of accuracy (Dikow et al., 2015; McKnight et al., 2017).

As a result, the accuracy of the information reduces the number of opportunistic suppliers and increases the profit of coordinators. However, the effectiveness of the two different partner-selection strategies is not equal. The increased accuracy of the information leads to a reduction in penalty costs for coordinators in both groups. The impact of the reduced opportunism is applied differently to the two strategies, as shown in Figure 5-11. As Information Quality improved, the effect of reducing penalty cost was more evident with the reputation strategy than with trust-based strategy.

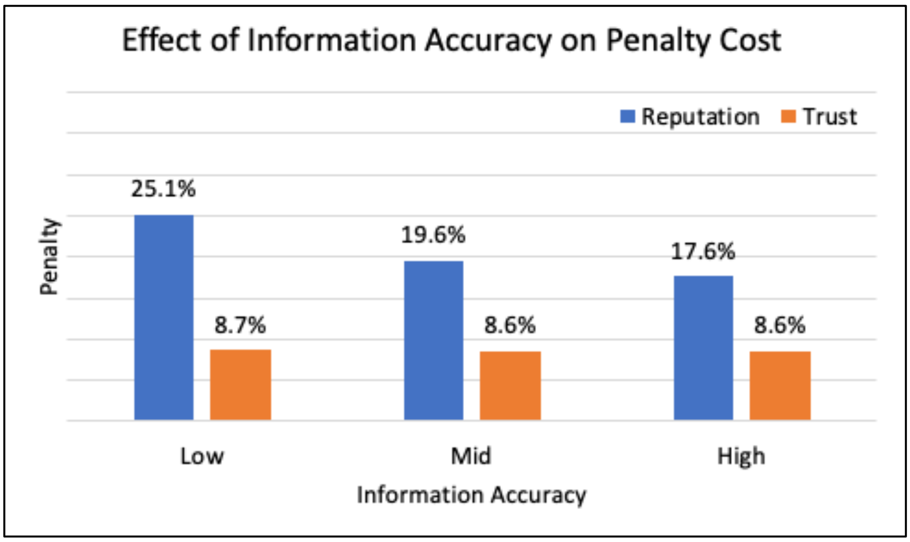


Figure 5-11 Simulation Results: Penalty Cost by Information Accuracy

5.3.3 Profitability by Information Accuracy

Figure 5-12 displays the change in profitability for two coordinator groups as the level of information accuracy increases from low to high. The profitability for the reputation-based strategy (represented in blue) shows a significant increase from 86.4% to 90.3% as the level of information accuracy improves. On the other hand, the opportunism level for the trust-based strategy remains unchanged at around 95% (represented in red) and there is little variation in the lines over the simulation period.

Figure 5-13 summarizes the final values for the long-term simulation results for the level of opportunistic suppliers for the two groups employing different strategies.

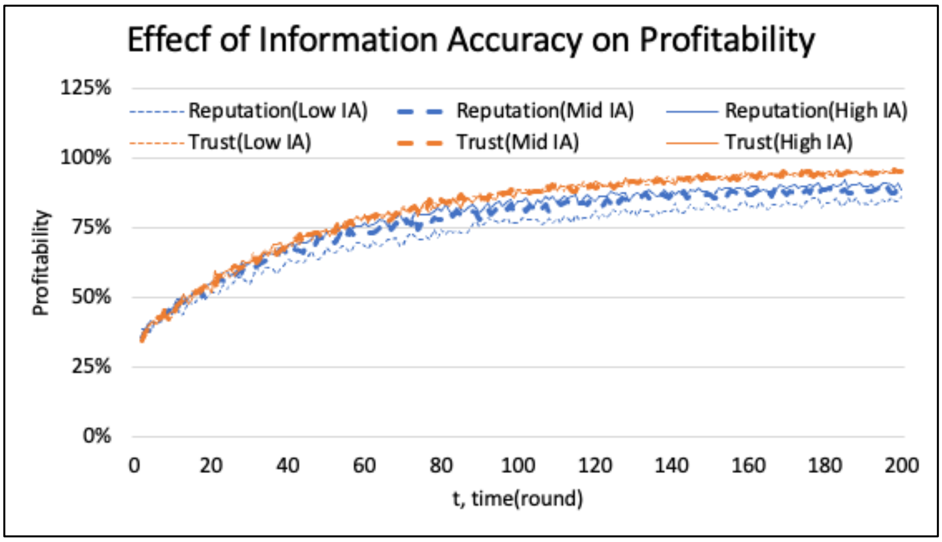


Figure 5-12 Simulation Results: Profitability by Information Accuracy

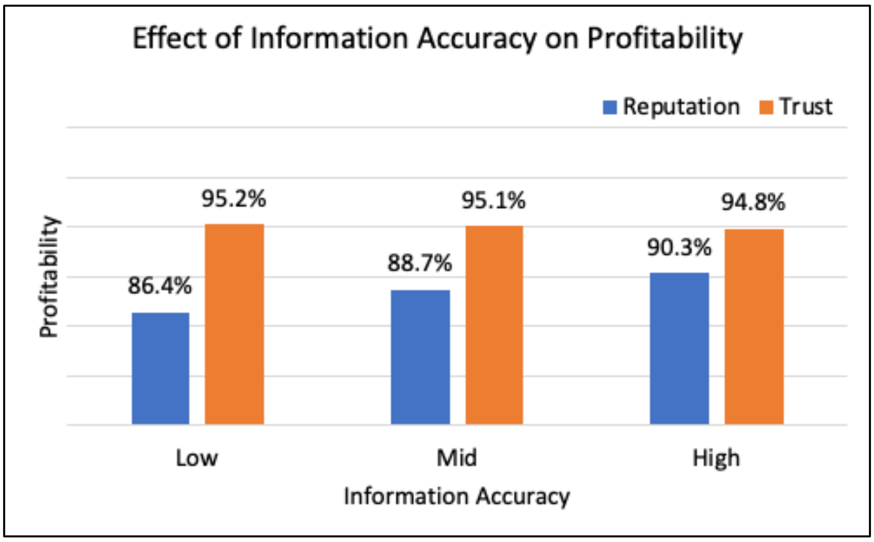


Figure 5-13 Simulation Results: Profitability by Information Accuracy

The change in the level of informational accuracy has a disproportionate effect on the network configuration of buyer firms with different partner-selection strategies. Figure 5-14 highlights the fact that the trust-based strategy experienced a negative change of -0.4%, indicating that the improvement in information accuracy had a negative impact on the trust strategy in comparison to the reputation strategy. This creates conditions where the performance of the trust strategy may deteriorate when competing with the reputation strategy.

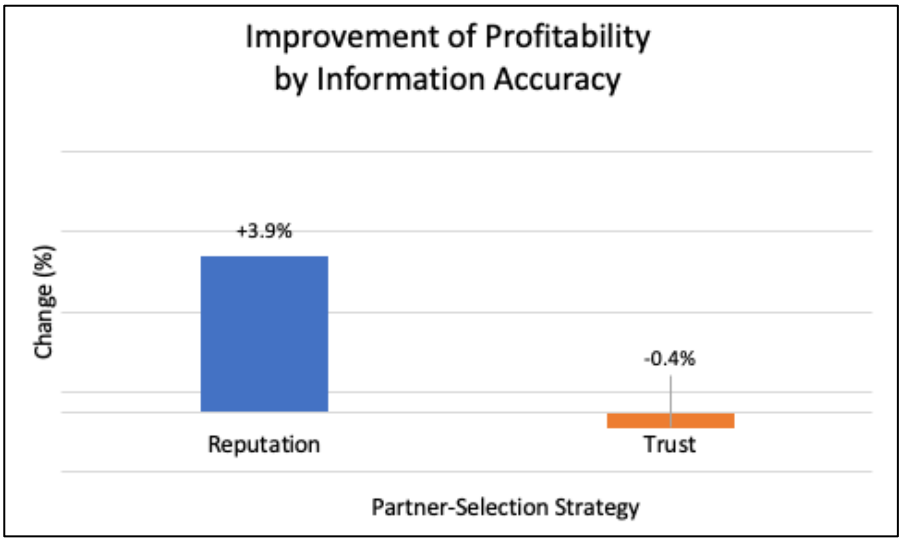


Figure 5-14 Improvement in Profitability by Information Accuracy

Generally speaking, selecting a supplier beyond one's familiar group using a reputation-based strategy is likely to be more costly than using a trust-based strategy (Goo *et al.*, 2007a; Kim and Chung, 2003). However, simulation results show that the cost of a reputation strategy does not need to increase linearly, and the increase in cost slows down when a sufficient number of reputational suppliers that can respond to market demand are identified. In other words, in a market with high information accuracy, a strategy that selects suppliers based on their reputation, as evaluated collectively, can prevent opportunism more efficiently and at a lower cost than a strategy that relies on repeated individual relationships to identify supplier behaviour.

Interestingly, the simulation results suggest that if these two supplier selection strategies compete in the market, coordinators who solely depend on existing suppliers for technology supply may not benefit from improved information accuracy and may struggle to retain their suppliers. Information accuracy results in a 7.5%-p improvement in overall profitability for the reputation-based strategy, while there is a 0.3%-p decline in the trust-based selection strategy (Table 5-3).

In a market where supplier information is accurately communicated to all buyers, a high-quality supplier can be presented with numerous opportunities regardless of the buyer's selection strategy. In particular, in a market where trustworthy suppliers are more readily available and offered more opportunities at a lower cost, it can be challenging for a buyer to continuously secure a specific supplier solely based on their past work. Hence, the simulation results support the notion of a 'trust premium' that incentivizes quality suppliers to maintain their service level on B2B digital platforms (F. R. Lin et al., 2005).

Finally, Table 5-3 summarizes the numerical results of Changing level of Information Accuracy at the low level of TU and the high level of MD.

Table 5-3 Simulation results: Effect of Information Accuracy

	Low IA		Mid IA		High IA	
	Reputation	Trust	Reputation	Trust	Reputation	Trust
Ties	23.5%	16.0%	20.4%	16.0%	19.2%	16.0%
Opportunism	27.6%	9.0%	21.1%	9.3%	18.6%	9.4%
Acquisition	16.4%	4.1%	12.4%	4.1%	10.6%	4.1%
Penalty	6.3%	2.2%	4.9%	2.2%	4.4%	2.2%
Profitability	84.8%	95.2%	88.7%	95.1%	90.3%	94.8%

5.4 Effect of Transaction Volume (Experiment 2 and 3)

This section examines the impact of Transaction Volume on the performance of two supplier selection strategies and also presents the interaction effect with the level of Information Accuracy.

5.4.1 Network size (Ties) by Transaction volume

Figure 5-15 illustrate the change in the network ties of two groups of coordinators as the level of Transaction Volume increased from a low level to a high level, while the level of Information Accuracy varied from low to high. When Information Accuracy is at a low level, the number of Ties for coordinators using the Reputation-based strategy (blue) shows an increase from 23.5% to 33.4% as the level of Information Accuracy increases from low to high. On the other hand, the number of ties for coordinators using the Trust-based strategy (red) increased moderately from 16% to 19.7%.

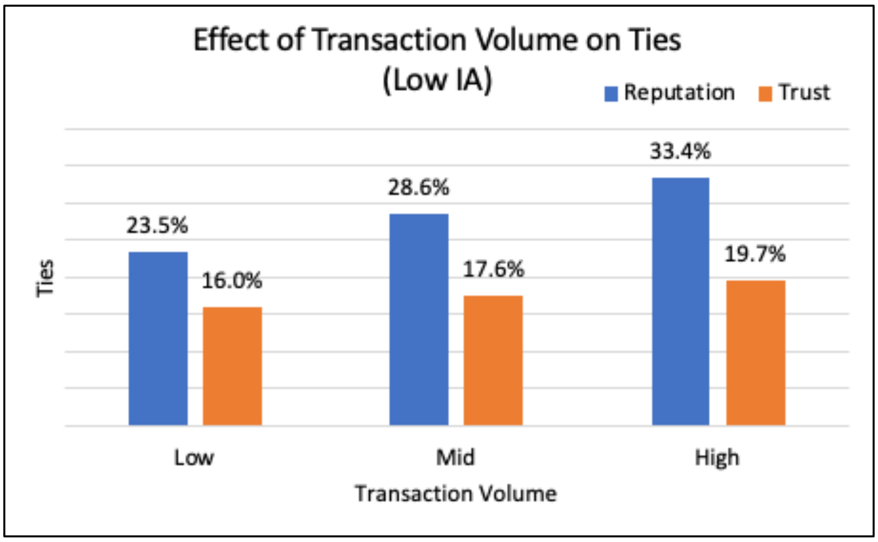


Figure 5-15 Simulation Results: Ties by Transaction Volume (Low IA)

In high-volume transaction markets such as B2B digital platforms, coordinators and suppliers interact more frequently, resulting in an increase in the number of network ties for each coordinator compared to low-volume markets, i.e. traditional marketplaces as denoted in this study. However, the impact is more pronounced in coordinators who employ a reputation-based strategy for supplier selection.

On the other hand, when Information Accuracy is high (Figure 5-16), the number of Ties for coordinators with a Reputation-based strategy (blue) increases from 19.2% to 26.4% as the level of Information Accuracy increases from low to high. Meanwhile, the number of ties for coordinators with a Trust-based strategy (red) increases moderately from 16% to 20.1%, remaining the same as the low level of Information Accuracy.

As predicted, coordinators from both strategies add more supplier ties as transaction volume (business opportunities) increases from a low, mid to a high level. However, in high accuracy markets, the number of network ties for coordinators with a reputation-based strategy increases more significantly, reducing the gap with coordinators using a Trust-based strategy, which is not influenced by information accuracy.

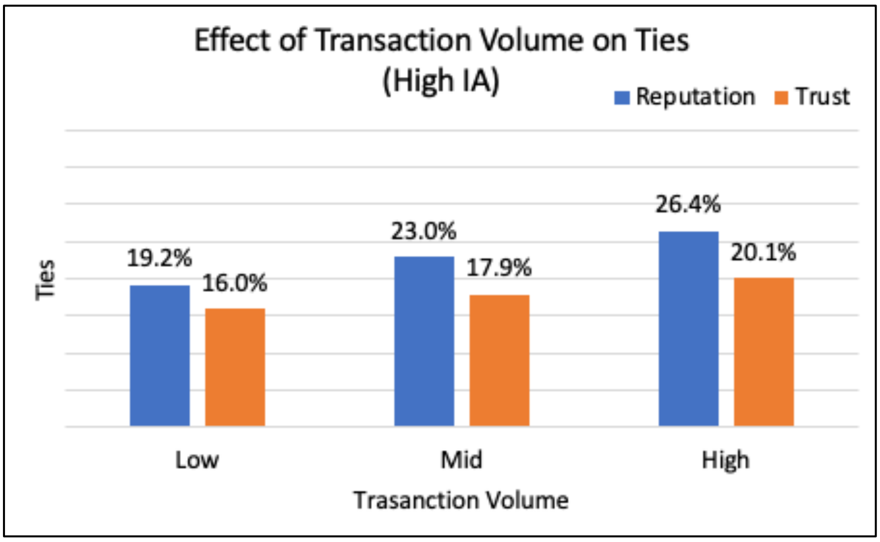


Figure 5-16 Simulation Results: Ties by Transaction Volume (High IA)

5.4.2 Opportunism by Transaction volume

Figure 5-17 compares the change in the level of opportunism for two groups of coordinators as the Transaction Volume increased from a low level to a high level while the level of Information Accuracy varied from low to high. When Information Accuracy is low, the opportunism for coordinators using the Reputation-based strategy (blue) decreases from 27.6% to 23.8% when the level of Information Accuracy increases from low to high. On the other hand, the opportunism for coordinators using the Trust-based strategy (red) decreases from 9.0% to 6.9%.

In markets with high transaction volume, coordinators and suppliers interact more frequently, which leads to more opportunities for coordinators to evaluate a wider range of suppliers in the market compared to low-volume markets. The increased interactions and evaluations help coordinators identify opportunistic suppliers during the bidding stage and reduce their participation in the consortium.

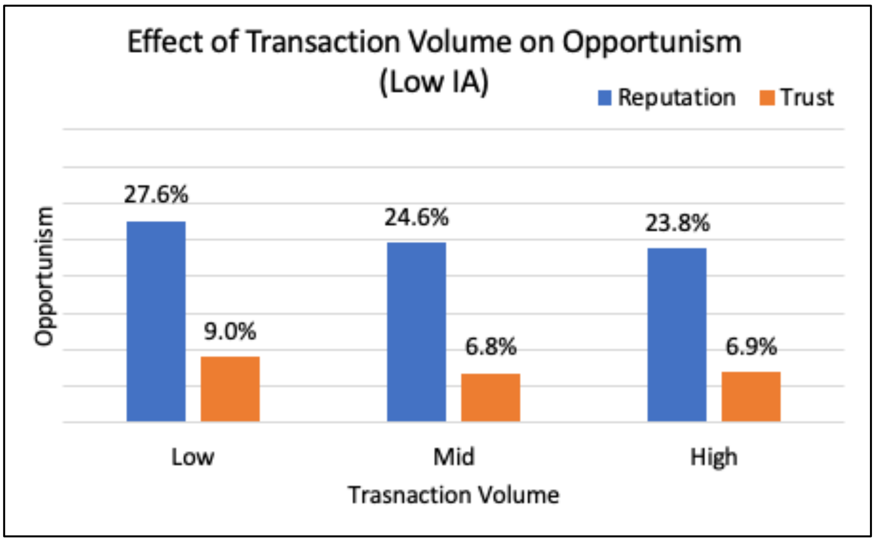


Figure 5-17 Simulation Results: Ties by Transaction Volume (Low IA)

Alternatively, when Information Accuracy becomes higher (Figure 5-18), the level of opportunism decreases for coordinators using the Reputation-based strategy (represented in blue bards), from 18.6% to 12.8% as the level of Information Accuracy increases from low to high. On the other hand, opportunism for coordinators using the Trust-based strategy (represented in red bars) decreases from 9.4% to 7.4%, showing a moderate increase from the case with a low level of Information Accuracy.

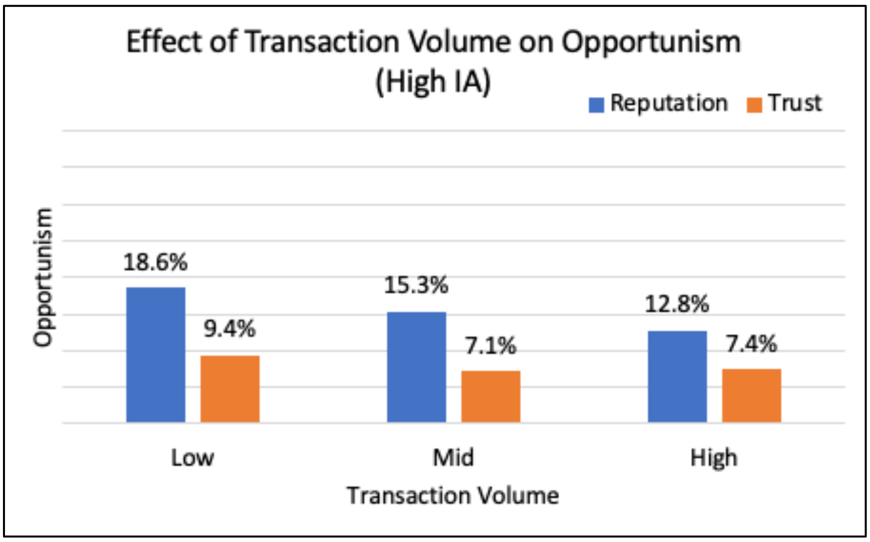


Figure 5-18 Simulation Results: Ties by Transaction Volume (High IA)

The results of the study indicate that as the transaction volume in the marketplace increases, both coordinators with reputation-based strategy and coordinators with trust-based strategy tend to reduce the level of opportunism in their consortium. This can be attributed to the increased frequency of interactions between coordinators and suppliers, leading to a more comprehensive evaluation of diverse suppliers in the marketplace.

However, in markets with high information accuracy, the reduction of opportunism for coordinators with a reputation-based strategy is more pronounced. This can be attributed to the higher reliability of reputational information in such markets, which enables coordinators to identify opportunistic suppliers more effectively during the bidding stage. The gap between coordinators with a reputation-based strategy and coordinators with a trust-based strategy in terms of reducing opportunism narrows as a result. In contrast, coordinators with a trust-based strategy are not significantly affected by the level of information accuracy and exhibit a moderate reduction in opportunism regardless of the level of information accuracy.

5.4.3 Profitability by Transaction Volume

Figure 5-19 compares the changes in the level of Profitability for two groups of coordinators as the transaction volume increases from a low level to a high level and the level of information accuracy varies from low to high. When the information accuracy is low, the profitability of coordinators with a reputation-based strategy (represented by blue bars) increases from 84.8% to 89.8% as the information accuracy improves from low to high. On the other hand, the opportunism of coordinators with a trust-based strategy (represented by red bars) increases from 95.2% to 96.5%.

In high-volume transaction markets such as B2B digital platforms, coordinators and suppliers interact more frequently, resulting in more opportunities for coordinators to evaluate the diverse suppliers in the marketplace, compared to low-volume markets. The expedited evaluation process enables coordinators to manage their network ties and opportunism more effectively.

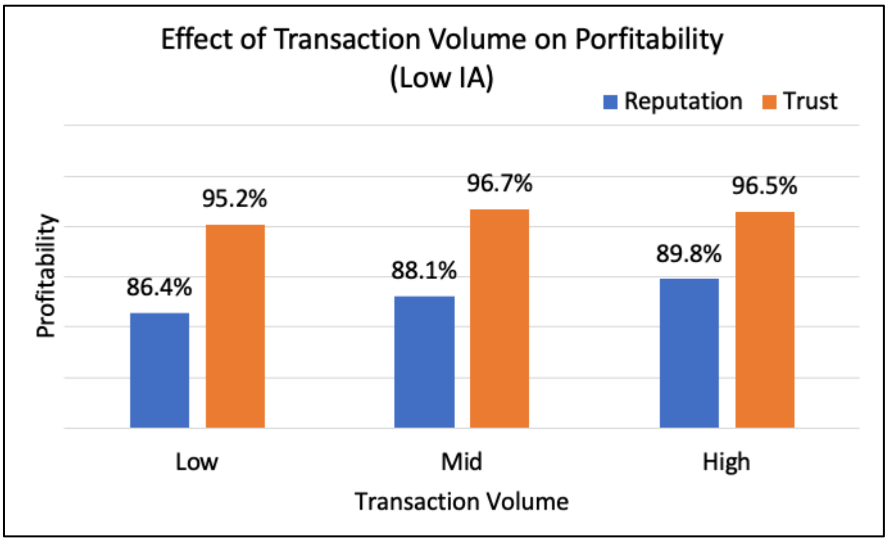


Figure 5-19 Simulation Results: Profitability by Transaction Volume (Low IA)

The change in transaction volume has a disproportionate effect on the performance of firms with different partner-selection strategies. As shown in Figure 5-20, the performance of the reputation-based strategy (blue) increased by 3.4%, while the trust-based strategy (red) increased by only 1.3%.

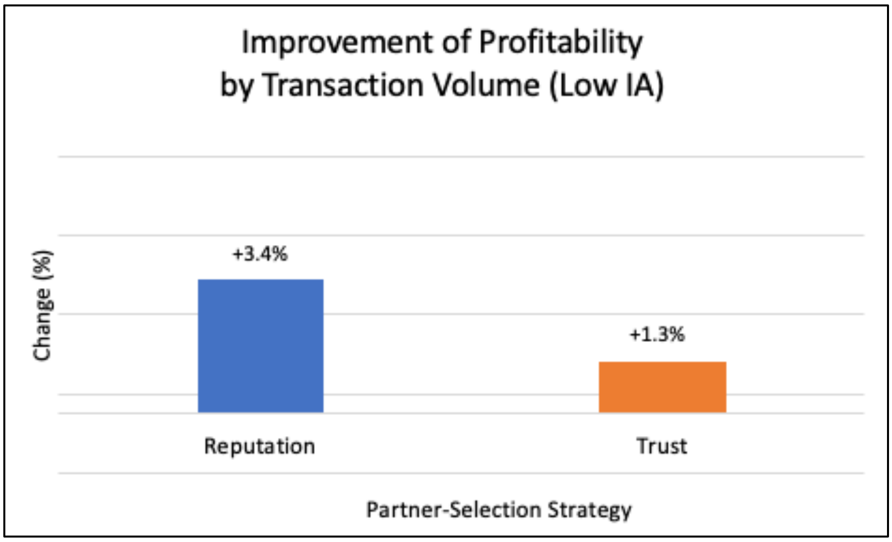


Figure 5-20 Improvement in Profitability by Transaction Volume (Low IA)

Alternatively, when information accuracy is high (Figure 5-21), the profitability of coordinators with a Reputation-based strategy (shown in blue bars) increases from 90.3% to 94.8% when the level of information accuracy increases from low to high. On the other hand, the opportunism of coordinators with a Trust-based strategy (shown in red bars) increases from 95.1% to 96.6% with no change observed at the low level of information accuracy. It is worth noting the significant difference in the performance (profitability) change between the two strategies with a rise of 4.5% for the Reputation strategy and only 1.5% for the Trust strategy as a result of changes in transaction volume.

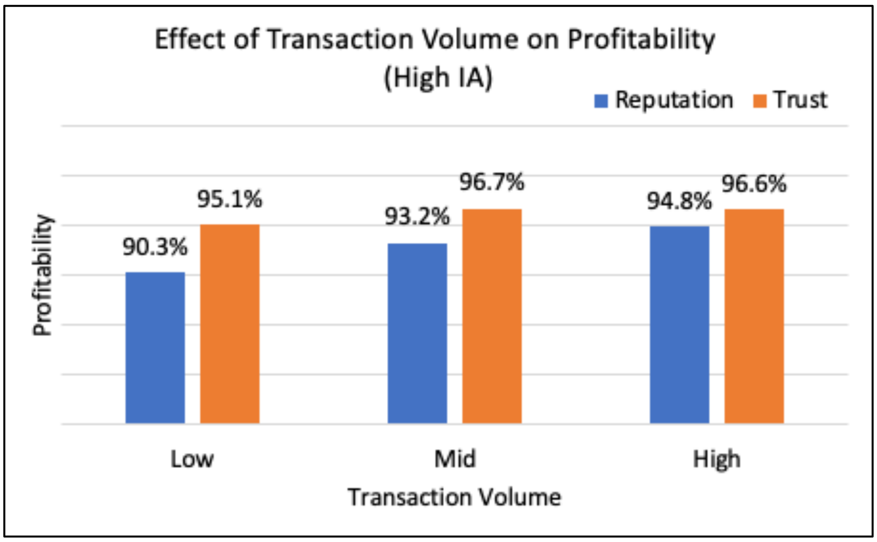


Figure 5-21 Simulation Results: Profitability by Transaction Volume (High IA)

Similarly, as at low levels of AI, simulation results suggest that changes in the level of transaction volume at high levels also significantly impact the performance of buyer firms with different partner selection strategies. As shown in Figure 5-22, the performance of the Reputation-based strategy increased by +3.5% while the Trust-based strategy only increased by +0.5% when information accuracy was also high.

Simulation results indicate that an increase in transactions within the platform has a positive indirect impact on the profitability of buyer firms in both groups. In markets where both the accuracy and volume of information are high, the profitability of the Reputation-based strategy improves and draws closer to the performance level of the Trust-based strategy, which is known for its cost-effectiveness through repeated partnerships.

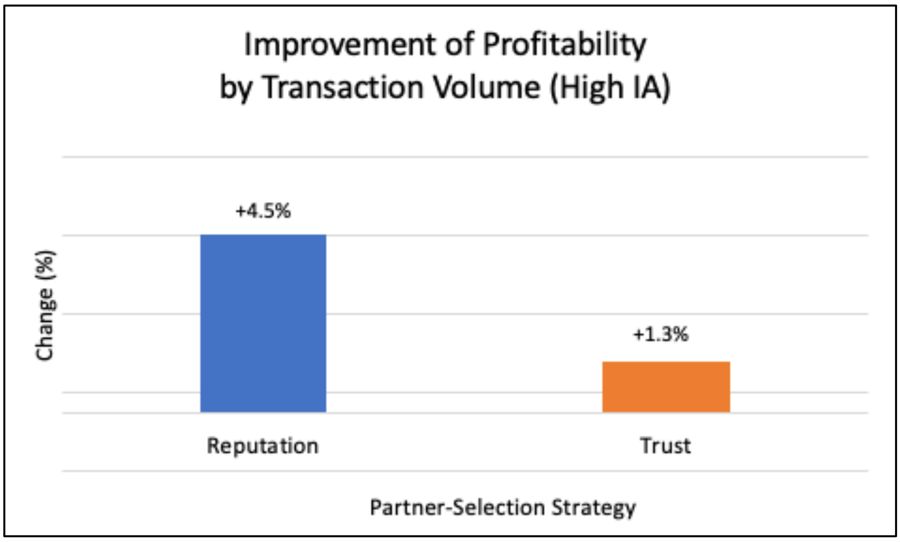


Figure 5-22 Improvement in Profitability by Transaction Volume (High IA)

When more suppliers are invited to ITO projects, more information about them becomes available after the completion of each project. This information is then shared with coordinators and helps them to make informed decisions and avoid opportunistic suppliers based on their partner selection criteria. The sharing of information is crucial as it allows coordinators to build a more accurate understanding of the suppliers and their abilities, reducing the risk of working with opportunistic partners.

Tables 5-4 and 5-5 summarize the numerical results of the simulation at increasing levels of transaction volume at Low Information Accuracy and High Information Accuracy, respectively. The results provide an in-depth analysis of how the increase in transactions affects the performance of buyer firms with different partner selection strategies, making it easier for organizations to make informed decisions about their partner selection criteria.

Table 5-4 Effect of Transaction Volume: High Information Accuracy

Volume	Low TV		Mid TV		High TV	
	Reputation	Trust	Reputation	Trust	Reputation	Trust

Ties	23.5%	16.0%	28.6%	17.6%	33.4%	19.7%
Opportunism	27.6%	9.0%	24.6%	6.8%	23.8%	6.9%
Acquisition	16.4%	4.1%	12.0%	2.8%	9.8%	3.3%
Penalty	6.3%	2.2%	5.7%	1.6%	5.4%	1.7%
Profitability	84.8%	95.2%	88.1%	96.7%	89.8%	96.5%

Table 5-5 Effect of Transaction Volume: High Information Accuracy

Volume	Low TV		Mid TV		High TV	
	Reputation	Trust	Reputation	Trust	Reputation	Trust
Ties	19.2%	16.0%	23.0%	17.9%	26.4%	20.1%
Opportunism	18.6%	9.4%	15.3%	7.1%	12.8%	7.4%
Acquisition	10.6%	4.1%	7.2%	3.0%	6.2%	3.3%
Penalty	17.6%	8.8%	21.8%	9.5%	23.5%	13.4%
Profitability	90.3%	95.1%	93.2%	96.7%	94.8%	96.6%

5.5 Effect with Technical Unpredictability (Experiment 3)

This experiment investigates the impact of Technological Unpredictability (TU) on two supplier-selection strategies. TU is one of the two major uncertainties in ITO transactions with Measurement Difficulty (Lacity et al., 2010) modelled in this study.

The high unpredictability of technological demand forces coordinators using both supplier-selection strategies to search for new suppliers with new skills. As a result, buyers are forced to work with new suppliers they have never worked with before, which increases the possibility of supplier opportunism and results in decline in alliance performance.

Figure 5-23 shows how the profitability of the two selection strategies changes as the level of Technological Unpredictability increases from low to high. In a setting with high IA and low TV, coordinators with both Reputation and Trust-based strategies achieved profitability of 90.3% and 95.1%, respectively, when TU was low. However, when TU became high, the profitability of coordinators using these strategies decreased to 77.6% and 71.2% respectively. The simulation results reveal that buyers using the trust-based strategy are more vulnerable to the effects of TU, and the damage is greater than for coordinators using the reputation-based strategy.

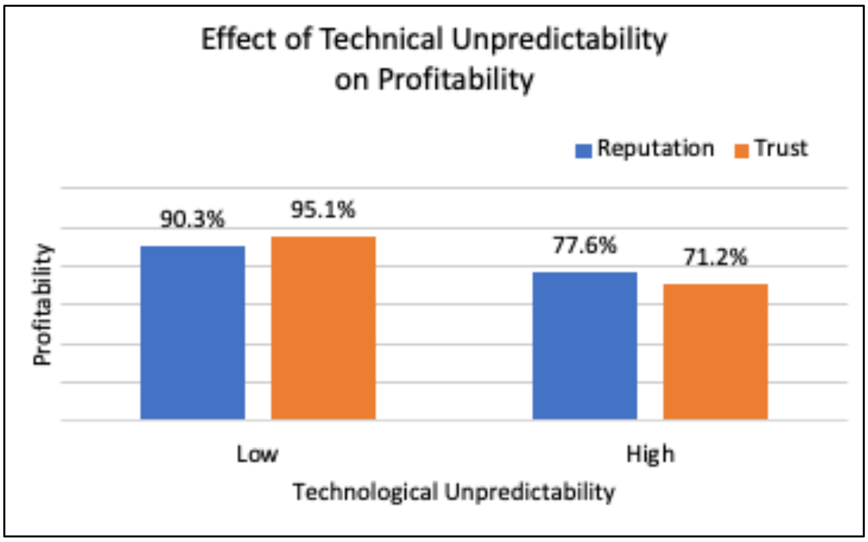


Figure 5-23 Simulation Results: Profitability by Technological Unpredictability

In this analysis, we determine robustness by calculating the profitability ratio of each strategy in high and low TU conditions, which indicates how well the strategy can maintain profitability despite TU changes. The Gap (p) in the final column indicates the difference in robustness between the reputation and trust strategies. Table 5-6 summarises the profitability of Reputation and Trust strategies at full factorial points of IA, TV, and TU, with MD remaining at the low level. The experimental results demonstrate that the gap in robustness against Technological unpredictability is greatest when information accuracy and transaction are both high.

Reputation mechanism is more effective in a market where participants share information about past transactions and have access to accurate information A centralised reputation management system in B2B digital platforms enhances the flow of information and credibility on the platforms (Ba and Pavlou, 2002; Bolton et al., 2004). Selecting suppliers based on their reputation rather than a relationship is the best way to take advantage of this enhanced flow of information. The strategy of continuously seeking out new suppliers based on reputation may entail more expenses in the selection, evaluation, and contracting process compared to quickly repeating contracts with existing partners. Nevertheless, this approach is more resilient to technological uncertainty than a trust-based strategy.

Table 5-6 Effect of Information Accuracy on Profitability by TU

Settings		Reputation Strategy			Trust Strategy			Gap (p)
Infor. Accuracy	Trans. Volume	Low TU	High TU	Robust-ness	Low TU	High TU	Robust-ness	
Low	Low	84.8%	68.4%	80.7%	95.2%	71.7%	75.3%	5.3%
	High	89.8%	77.1%	85.9%	96.5%	77.1%	79.9%	6.0%
High	Low	90.3%	77.6%	85.9%	95.1%	71.2%	74.9%	11.1%
	High	94.8%	84.6%	89.2%	96.6%	74.3%	76.9%	12.3%

Table 5-7 summarises the success rates of consortium formation in high TU conditions. A coordinator's consortium formation is deemed successful if they locate all the necessary suppliers and form a consortium. Conversely, if all the required skills (or suppliers) can not be outsourced in time, the consortium formation will fail, and the coordinator will not receive any rewards from the business opportunity in the simulation round. As the uncertainty of technology increases and the demand for new technology increases, competition may arise among coordinators for the new technologies. As a result, two strategic groups demonstrate a difference in their ability to secure new technologies and suppliers. This disparity between the two strategies is more prominent in markets with higher information accuracy and higher transaction volume.

Interestingly, the results also reveal that the relative weakness of the relationship strategy results partly from overreliance on existing partners. In particular, where market requirements change rapidly, excessive reliance on past partners can cause a lag in the competition to acquire new knowledge or partners (Gargiulo and Benassi, 2000; Gilsing et al., 2014a) and offset the cost-benefit from maintaining a relationship with known suppliers (Yamakawa et al., 2011). A lack of flexibility and efficient information infrastructure can hinder the growth of buyers adopting the dyadic trust-based strategy (Gulati, 1995; Poppo and Zenger, 2002; Uzzi, 1997).

Table 5-7 Successful formation of Consortium at High TU

Infor. Accuracy	Trans. Volume	Reputation	Trust	Gap (p)
Low	Low	95.6%	91.4%	5.3%
	High	92.6%	85.8%	6.0%
High	Low	96.3%	90.2%	11.1%
	High	93.8%	83.5%	12.3%

5.6 Effect of Measurement Difficulty (Experiment 4)

This experiment investigates how the partner-selection strategies are affected differently by Measurement Difficulty (MD) is one of two major uncertainties surrounding ITO transactions (Lacity 2010) modelled in this study.

In situations where the evaluation of technology provided by a supplier is difficult to measure the quality, feedback provided by the buyer makes it difficult to accurately determine whether the supplier is opportunistic or cooperative at the end of project. Consequently, buyers are more likely to continue to choose opportunistic suppliers.

Figure 5-24 shows how the profitability of the two selection strategies changes as the level of MD increases from low to high. When MD is low, two coordinator groups with Reputation and Trust-based strategies achieve 90.3% and 95.1% respectively. However, the profitability of coordinators decreases to 65.0% and 65.8% respectively for Reputation and Trust-based selection strategies when the level of MD becomes high.

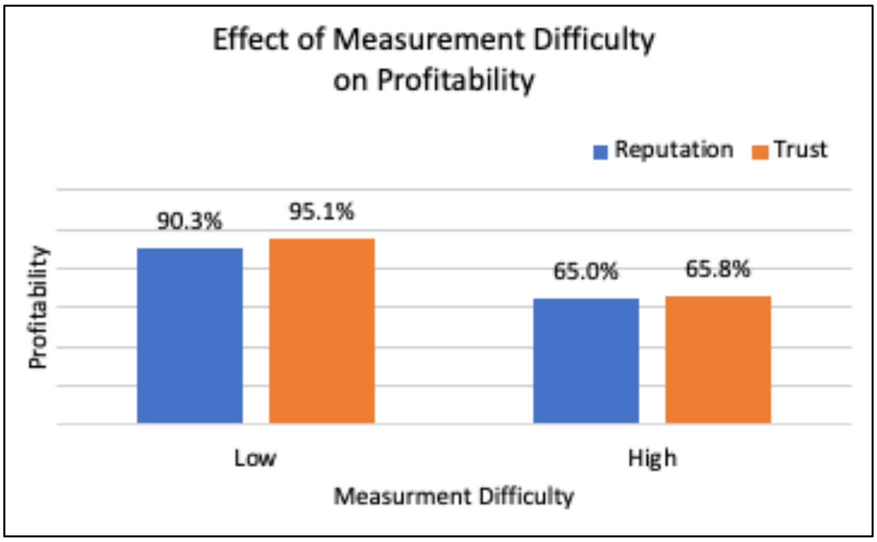


Figure 5-24 Simulation Results: Profitability by Measurement Difficulty

Table 5-8 summarises the profitability of the Reputation and Trust strategies at various levels of IA, TV, and MD, while TU is fixed at a low level. Both strategies showed a gradual increase in robustness against MD as IA and TV increased. The enormous Gap in robustness over the change of Measurement Difficulty was observed when both information accuracy and transaction volume were high. However, the difference between the two strategies was smaller than in robustness against TU compared to Table 5-6.

Interestingly, when IA was low, the difference in robustness between the reputation and trust strategies was negative, with values of -2.1%p and -1.1%p for low and high TV conditions, respectively. This outcome suggests that a trust-based strategy may be more effective for high MD transactions in a market with relatively low information accuracy, such as traditional marketplaces.

Table 5-8 Robustness against Measurement Difficulty

Settings		Reputation Strategy			Trust Strategy			Gap (p)
IA	TV	Low MD	High MD	Robust-ness	Low MD	High MD	Robust-ness	
Low	Low	84.8%	56.4%	*66.5%*	95.2%	65.3%	*68.6%*	-2.1%
	High	89.8%	64.6%	*71.9%*	96.5%	70.5%	*73.1%*	-1.1%

High	Low	90.3%	65.0%	*72.0%*	95.1%	65.8%	*69.2%*	2.8%
	High	94.8%	73.4%	*77.4%*	96.6%	71.8%	*74.3%*	3.1%

Measurement difficulty (MD) does not seem to affect the performance of the two strategies as much as TU. As shown in the high TU results (Table 5-7), the profitability gap was up to 12%, but in the case of MD (Table 5-8), the largest gap in robustness against MD decreases to 3.1%p when information accuracy and volume are both high.

5.7 Sensitivity Analysis

To verify the simulation model, a sensitivity analysis was conducted by varying critical parameters, including market size (number of participants), acquisition costs, and penalty rates. The results of this sensitivity analysis are presented in Appendix C. While the details of the results are not presented here, it was found that the primary findings remained robust even when these parameters underwent moderate variations.

The most notable observation is that, unless the penalty cost is exceptionally low, specifically at 25% of the defective amount in the base scenario as shown in Figure C-3, the group employing reputation-based selection cannot surpass the performance of the relationship-based group. In all other parameter variations, the relationship-based selection group consistently outperforms, primarily due to the cost-effectiveness of maintaining relationships with trusted suppliers.

5.8 Summary

In this chapter, the design of experiments was presented in order to analyse the performance of partner-selection strategy in B2B digital platforms, and the base model was validated against relational network theory and ITO empirical findings. Findings from the simulation are summarised as follows:

Firstly, the choice of partner-selection strategy is a strategic decision for buyers due to its differential potential to reduce supplier opportunism and transaction cost associated with uncertainties. The experiments demonstrate that buyer firms with the partner selection based on mutual trust can be cost-efficient in both acquisition and opportunism control when uncertainties are low. Buyer firms with a reputation-based selection strategy have a greater risk of encountering more opportunistic suppliers as it expands their supply network borders faster. This study reassures that the relative performance of two strategies can vary by nature and level of uncertainties, which complies with findings from experimental studies. Table 5-9 compares the relative performance of two partner-selection strategies at various levels of ITO uncertainties in traditional marketplaces (assuming low levels of IA and TV). For example, a reputation-based strategy can be more suitable when the market faces fast-changing technologies, while a trust-based strategy can be more effective in avoiding opportunism when buyers experience difficulties in measuring the quality of provided services.

Table 5-9 Performance of Partner-selection strategy against ITO uncertainties

High TU	Reputation > Dyadic Trust (Figure 5-23)	-
Low TU	Reputation < Dyadic Trust (Table 5-2)	Reputation < Dyadic Trust (Figure 5-24)
Levels	Low MD	High MD

Secondly, the experimental results suggest that in markets where information accuracy is high, a reputation-based strategy can more quickly and cost-effectively form a collective pool of reputational suppliers to provide the necessary skills to project coordinators. However, paradoxically, it was found that increased information accuracy could be rather unprofitable for the dyadic trust-based strategy that pursues cost efficiency through the continuation of the relationship. Unlike traditional markets, the information of loyal suppliers is quickly disclosed to the entire market, creating more business opportunities than continued opportunities in existing relationships. In particular, in markets where there is competition to acquire the rare technology of suppliers, it was shown that the buyer must pay a higher premium to maintain the constant availability of the demanded technology. The findings reveal a new boundary condition of dyadic trust by showing that it impedes the cost-effectiveness of the relationship strategy. The information accuracy and its opposite relationship between the two strategies partly answer why digital platforms adopt reputation systems and more companies are less hesitant to seek new suppliers beyond the bounds of their past relationships. Therefore, the analysis of the mechanism by which information accuracy can have an opposite relationship depending on the selection strategy partially answers the question, "Why do most digital platforms adopt reputation management systems, and why are more companies becoming less hesitant to seek new suppliers beyond the bounds of past relationships?"

Thirdly, the simulation findings suggest that in digital platforms with a higher transaction volume, both buyers and suppliers can benefit from increased profitability. The success of a reputation-based strategy is more reliant on the transaction volume than a dyadic-trust strategy. Greater transaction frequency facilitates more substantial information generation, including supplier behaviour, and contributes to the formation of a pool of reliable suppliers that buyers can choose from without encountering unknown suppliers.

Table 5-10 compares the relative effectiveness of two partner-selection strategies based on various levels of Information Accuracy and Transaction. In this study, it is assumed that information accuracy (IA) and transaction volume (TV) in the digital market are generally higher than those in the traditional market. Therefore, the top right area of the table, representing high IA and high TV, is associated with the digital market, while the bottom left area, representing low IA and low TV, represents the traditional market.

Table 5-10 Performance of Partner-selection strategy

B2B digital platforms vs Traditional marketplaces

High TV	Reputation > Dyadic Trust (Figure 5-20)	Reputation > Dyadic Trust (Figure 5-22)
Low TV	Reputation < Dyadic Trust (Table 5-2)	Reputation > Dyadic Trust (Figure 5-14)
	Low IA	High IA

Chapter 6 Discussion

Chapter 6 provides a discussion of the findings and contributions presented in the current study. The proposed research model helps illustrate the role of IT-based reputation system in B2B digital platforms and sheds a light on explaining the relative advantage of the reputation-based strategy over the mutual trust-based strategy. Information Quality and Information Quantity reduce the technological uncertainty associated with suppliers' reputations and lead to the reduction of opportunism and transactional costs in B2B digital platforms. The simulation results also demonstrated differentially affecting the performance of reputation and mutual trust as a partner-selection strategy by the nature and level of technological uncertainties.

6.1 Theoretical Contributions

The purpose of this study was to examine the relative advantage of two partner-selection strategies in B2B digital platforms and propose an analytical explanation for the prevalence of the reputation mechanism as partner-selection strategy in B2B digital platforms. The researcher developed a model that traces the change of variables affecting profitability of buyers by taking a distinctive supplier selection strategy. The findings of this research complement and extend the existing literature in the following three research areas: IS on the partner-selection strategy, B2B digital platforms and relational theory and contribute with propositions (new theories) as follows.

Partner-selection mechanism

Our main contribution is being the first study to systematically analyse how Information Quality and Information Quantity in B2B digital platforms differentially influence the performance of buyer firms' partner-selection strategies. From the perspective of buyers, the findings explained well the successful transition to B2B digital platforms with IT-based reputation systems from the traditional supply chain network by providing analytical evidence of curving supplier opportunism while simultaneously reducing acquisition costs.

Prior studies suggested that the partner selection strategy is determined by buyers to respond to the nature and level of uncertainties in the market (Beckman et al., 2004; Gilsing et al., 2014b; J. Oh, 2013), i.e. volatility and ambiguity (S. J. Carson *et al.*, 2006).

For example, Beckman et al. (2004) investigate how firms change their partner-selection strategy in response to different types of uncertainty. The research suggested that firms are likely to reinforce and extend their network partners to deal with market uncertainty and firm-specific uncertainty, respectively. Other studies argue that a partner selection strategy is taken according to the purpose of the alliance strategy to be fulfilled. For example, Yamakawa (2004) argues that firms tend to continue relationships with the same partners for cost-leadership strategy while exploring new partners for differentiation from competitors.

In addition to the literature in the research area of partner-selection strategy, this research improves an understanding of how the performance of Trust and Reputation as a partner-selection mechanism can be affected by the Information Quality and Information Quantity of the marketplace.

Simulation results revealed that as transactions and buyers' evaluations continued, a group of reputable suppliers was identified in the market to form a pool. Buyers who seek reputable suppliers tend to engage with suppliers from a pool of repeat partners, thereby decreasing the necessity of finding new partners, minimising uncertainty, and lowering the cost of acquiring new partners.

As repetitive transactions with a group of reputational suppliers became possible, the effect of reducing acquisition cost, which was an advantage of the relationship-based strategy, could also be obtained from the reputation strategy. In other words, the expansion of a trust-based dyadic (1-to-1) relationship into a multi-to-multiple relationship in a reputation-based strategy enables the reduction of unnecessary acquisition costs and rapid response to technological changes. The pooling effect of this reputation strategy is found to be stronger as (**Proposition 1**) the accuracy of the information of the channel through which reputation is transmitted increases and **(Proposition 2)** the number of transactions that determine the quantity of Information increases. This study suggests that the centralised supplier reputation management system based on information technology identifies (pools) reputational partners by increasing the efficiency in distributing accurate information, lowers the buyer's partnership cost for buyers and improves their profitability, thereby increasing trust in the market.

Relational network theory

This study adds to the existing literature on relational governance in several ways. Previous studies have established the value of relational governance as a means to mitigate partner opportunism and have demonstrated that it can improve mutual trust and commitment, leading to better alliance performance (Poppo and Zenger, 2002). Additionally, by reducing the costs associated with searching for and managing new partners, relational governance has been shown to enhance firm profitability (Goo et al., 2007). Other scholars have explored boundary conditions in which the relevance of relational governance decreases, such as in rapidly changing markets (Gilsing et al., 2014b) or when agent risk is low (Meuleman et al., 2010).

In this study, the simulation results suggest that the cost benefits associated with maintaining relationships with old suppliers may be offset by the added cost of maintaining a royal supplier's availability when digital platforms expose a reliable supplier's reputation to the wider marketplace, offering more opportunities from diverse buyers. The research results uncover the limitations of trust-based relational governance approach to selecting partners by combining insights from relational network theory and cost analysis. As the accuracy of Information in the market increases and more information becomes available through more transactions, reliable suppliers will be perceived as a reputation group in the market, and the business opportunities available will expand not only through dyadic relationships but also through unfamiliar buyers who pursue reputation **(Proposition 3)**. Therefore, as a supplier with a broad demand base no longer relies on a relationship with a specific buyer, it is implied that if the buyer wants to acquire the necessary technology through individual relationships with such a supplier, an opportunity cost for waiting may be incurred.

B2B digital platforms

This research contributes to the B2B digital platform literature by building a computational model and examining the performance change of buyers according to their supplier-selection mechanisms which are regarded to be important in B2B digital platform studies. The proposed model operationalises important attributes of B2B digital platforms distinguished from traditional marketplaces to have a better understanding of how reputation mechanisms the partner-selection strategies.

One of the novel features of this simulation research is an integrated model based on transaction cost analysis, social capital and relational exchange theory to analyse the relationship between informational attributes of B2B digital platforms and the performance of buyers in terms of cost and profitability. The proposed cost model for acquiring new suppliers and dealing with opportunistic suppliers allows for a detailed examination of the performance of two different strategies under different market conditions.

6.2 Managerial implications

B2B platform operators can utilise the results of research to improve the competitiveness of their platform. The quality of information accuracy can significantly impact the performance of buyers, and therefore, platform operators need to continuously optimise the efficacy of platform information systems from customer accessibility to reporting system to provide buyers with accurate information for better decision-making. This includes providing tools such as feedback templates that assist customers in entering supplier behavioural information more efficiently and accurately after a transaction has taken place. In the digital age where business dealings are conducted online, the pace of technological innovation is rapid, and it becomes challenging for the buying side to have a complete understanding of the supplier's behaviour and provide accurate feedback. This is particularly evident in online B2B platforms where the distance between buyers and suppliers can make it difficult to get a clear picture of the supplier's behaviour (McKnight et al., 2017).

To further enhance buyers' trust, platform operators can develop an advanced supplier selection support system by analysing the nature and level of business uncertainties for ITO transactions. Simulation results show that the relative performance of the selection algorithm may vary on the imposed uncertainties on each transaction. Experimental results suggest that if the technology provided by the supplier is difficult to evaluate accurately from the buyer's perspective, it is advantageous to continuously obtain technology from a reliable supplier based on past experiences instead of looking for a reputational supplier who has not worked with one before. This implies that a different partner-selection strategy can be applied according to the characteristics of the required technology.

To further enhance buyers' trust, managers in B2B platform providers can take the initiative to develop a sophisticated supplier recommendation system that takes into account the nature and level of uncertainties involved in ITO transactions. The system would be based on simulations and experiments that would give insight into how the performance of the selection algorithm could be affected by different levels of uncertainties in each transaction. For instance, as simulation results suggest, when the degree of technology change and measurement difficulty is not so high, it may be more cost-effective for buyers to maintain a relationship with a trusted supplier rather than seeking out reputable suppliers and paying additional costs of search and evaluation. This highlights the importance of adopting a flexible and adaptable partner-selection strategy, considering the unique characteristics and requirements of the technology being sought.

The impact of transaction volume highlights the importance for new platform operators to offer incentives to early adopters and encourage an increase in buyer-supplier transactions. This not only provides buyers and suppliers with access to more diverse business opportunities but also helps to establish trust in the supplier information provided by the platform’s reputation systems. Simulation results indicate that as the quantity and quality of information improve, buyers can experience a lower transaction cost and a greater chance of finding suitable suppliers, leading to a higher return on investment. The combination of lower costs and improved trust mechanisms may encourage buyers to shift from traditional supplier-buyer marketplaces to digital platforms.

6.3 Summary

This part has provided a discussion of the findings in relation to existing literature. In so doing, this part has addressed the research aim and objectives of this study, that is, to shed light on how the reputation-based choice of supplier in B2B digital platforms became dominant over the trust-based mechanism. As such, this has highlighted contributions to research on the role of Information Systems in B2B digital platforms as supplier-selection strategy.

Chapter 7 Conclusion

Chapter 7 reviews the overall summary of the research, limitations and future research directions of this study.

7.1 Research Summary

In ITO partnership research, supplier opportunism and externalities have long been the most studied topics (Goo *et al.*, 2007a; Lacity *et al.*, 2010; Poppo and Zenger, 2002; Ravindran *et al.*, 2015). Relational exchange theory and social capital suggest that an informal mechanism using mutual trust formed through repeated relationships and trust acquired from various networks is effective in suppressing partners' opportunism(S. J. Carson *et al.*, 2006; Granovetter, 1985; Poppo and Zenger, 2002; Uzzi, 1996). Empirical findings in the strategic management studies suggest that a partner-selection strategy either exploitation or exploration can better deal with different uncertainties and help organisations meet their strategic needs (Beckman et al., 2004; Gilsing et al., 2014a; Yamakawa et al., 2011). Similarly, the B2B digital platforms literature has provided vast information on the role of reputation system, information quality and their cost advantage over traditional marketplaces (Bolton *et al.*, 2004; Chakravarty *et al.*, 2014; Zheng *et al.*, 2019). However, little research on what features of B2B platforms and how they influence the effectiveness of two distinctive selection mechanisms (network reputation and dyadic trust), to the best of our knowledge, has not been meaningfully investigated.

This study aims to answer the following research questions by analysing the impact of market attributes and uncertainties on the performance of two partner selection strategies.

- What factors in digital markets can make the performance of a partner selection strategy different from traditional markets?
- How do the two attributes of B2B digital platforms, Information Accuracy and Transaction Volume, affect the performance of different buyers with different supplier-selection strategies?

This study posits that the ‘information quality’ and ‘transaction volume’ affect the relative performance between ‘reputation’ and ‘trust’ as a partner-selection mechanism as more B2B transactions move on digital platforms.

A simulation approach was taken to find answers to the research questions. A simulation approach can appropriately demonstrate the behaviour in a buyer-supplier network and the performance which is the consequence of their interactions among actors and environmental conditions(Harrison et al., 2007; Hauser et al., 2017). Based on the theory of transaction cost and social capital, a simulation model was proposed to analyse the effect of B2B digital platforms on the partner-selection strategy based on the long-term transactional cost in the ITO context. The simulation approach enabled an analysis of investigation on the long-term interactions in buyer-supplier networks based on two selection strategies, the moderating effect of uncertainties (technological unpredictability, measurement difficulty) and attributes of marketplaces.

The findings of this research complement and extend the existing literature in the following three research areas: strategic management on the partner-selection strategy, B2B digital platforms and relational exchange theory.

Firstly, the research improves an understanding of how the performance of Trust and Reputation as a partner-selection mechanism can be affected by the Information Quality and Information Quantity of the marketplace. The simulation results in this research visualized a mechanism that the coordinators selecting their suppliers' reputations effectively can reduce the risk of supplier opportunism by identifying and sharing a pool of trusted suppliers collectively. Interestingly, the performance of trust-based strategy may decline as the relation-based strategy can incur extra costs in maintaining a stable sourcing pool where a good supplier is offered more opportunities by diverse buyers.

Secondly, one of the key novel features of this simulation research is the integrated model based on TCE, social capital and relational exchange theory to analyse the relationship between B2B digital platforms and the performance of buyers in terms of cost and profitability. The proposed cost model for the acquisition of new suppliers and adverse selection of opportunistic suppliers enables an analytical study of the performance of two strategies analytically under different conditions of market uncertainties.

Finally, this research contributes to the relational network theory by revealing another boundary condition to the partner selection strategies. The simulation results suggested that relational governance is less competitive for selecting partners when the information accuracy of a marketplace is high and opportunities are abundant, allowing firms to expand their networks out of a relational pool. Furthermore, reputational capital may act as a partial substitute for relational embeddedness, again permitting firms to expand their networks.

7.2 Limitations of this research

A simulation is an implementation of a simple model to create or extend a model, but the simple model itself may have multiple theoretical concepts in a complex way (Davis et al., 2007; Harrison et al., 2007). The simulation model proposed in this study adopts a somewhat simplified view by conceptualising a marketplace as a series of interactions among actors with one key strategy. For example, two strategies for buyers (reputation vs trust) and two-behaviour model (cooperative vs opportunistic) for a supplier, and the researcher acknowledges that interaction of buyer-supplier, as a whole, is a much more complex, dynamic process and multiple conceptions of antecedents and consequence of the behaviours exist in the literature (Granovetter, 1985; Hawkins *et al.*, 2008; Lacity *et al.*, 2010).

While simulation models offer several advantages, such as the ability to incorporate complex dynamics without being constrained by analytical tractability, and the ability to study long-term interactions, they are stylised theoretical models of reality that require rigorous empirical validation. The findings of this simulation study can be guaranteed to a certain degree as the related theories underlying the computation model in this study are supported by vast of empirical evidence (Davis et al., 2007).

The researcher also notes that any results derived from simulation research are firmly based on the construction of the simulation model. For example, the proposed model assumes that the selection strategy of buyers and supplier tendency of opportunism are independent. However, the real world is more reciprocal rather than one directional (Parkhe, 1993).

Furthermore, it is worth noting that partnership performance is a complex variable encompassing various dimensions, including innovation, satisfaction, information exchange, and partnership durations (Goo *et al.*, 2007a). In this study, our focus has been on evaluating performance through a transaction cost-based approach, and it is imperative to incorporate this perspective when applying our findings.

Moreover, the consequences of a simulation study can only be assessed for a particular set of parameters and assumptions. As a result, if the parameters are changed or the assumptions are violated, the research findings are unlikely to be valid.

Nevertheless, the analyses and findings do provide at least some important initial insights into the differential efficacy of two supplier-selection approaches in the context of B2B digital platforms as the models were based on a lot of empirical evidence from a topic that has been studied for a long time.

7.3 Future research directions

While this study provides a novel approach and insights to understand the role of B2B digital platforms on partner-selection strategies, the model offers potential extensions to generate further valuable comprehensions and intuitions on this topic.

Moreover, the findings of this study can lead to further hypotheses that enhance current knowledge in relational network theory and strategic management. The improvements of this research could be addressed by elaborating the unused features that are available in the current computer model. In the current model of opportunism, the behavioural tendency of a supplier is set as either opportunistic or cooperative and remains static during the period of each consortium. However, opportunism is a complex phenomenon with a multitude of antecedents and consequences supported by rich empirical evidence (Hawkins *et al.*, 2008). By examining the reciprocity of opportunism, which dynamically changes according to one's level of trust or prestige, the future study can provide a deeper understanding of the relationship between supplier-selection strategy and cooperation with suppliers.

Furthermore, simulation models of buyer-supplier cooperation can be widely applied to various studies of strategic partnership models. For example, in a public-funded R&D network, a coordinator may select participants to form a consortium and research optimal strategies to control opportunism. With the implemented simulation model, researchers can expect to gain insights into the role of network embeddedness on the cost-effectiveness of public-funded R&D program governance (Tripsas *et al.*, 1995).

Empirical testing is necessary to ensure the high external validity of this study. A long-term institutional study that traces transactions within large-scale marketplaces, where participants interact over an extended period, can provide a historical evolution of partner networks and financial performance. This can be compared to the simulation results in this study.

Due to the fact that the developed simulation model is based on a number of well-established theories and is backed by bodies of different perspectives, empirical tests are not likely to be a major issue in this study. However, one of the significant roles of a simulation study is to provide a basis for further empirical studies (Harrison *et al.*, 2007). Therefore, the findings of this research can be used as a foundation for the empirical examination of the effectiveness of two partner-selection mechanisms in different marketplaces (B2B, P2P digital platforms and traditional pipeline-like supply chain).

Bibliography

Akter, S. and Wamba, S. F. (2016). Big data analytics in E-commerce: a systematic review and agenda for future research, *Electronic Markets* 26(2): 173–194. Retrieved from https://link.springer.com/article/10.1007/s12525-016-0219-0

Albino, V., Carbonara, N. and Giannoccaro, I. (2007). Supply chain cooperation in industrial districts: A simulation analysis, *European Journal of Operational Research* 177(1): 261–280.

Anderson, E. (1988). Transaction costs as determinants of opportunism in integrated and independent sales forces, *Journal of Economic Behavior and Organization* 9(3): 247–264.

Artz, K. W. and Brush, T. H. (2000). Asset specificity, uncertainty and relational norms: An examination of coordination costs in collaborative strategic alliances, *Journal of Economic Behavior and Organization* 41(4): 337–362.

Axelrod, R. and Hamilton, W. D. (1981, March 27). The evolution of cooperation, *Science*. Retrieved from http://science.sciencemag.org/

Ba, S. and Pavlou, P. A. (2002). Evidence of the effect of trust building technology in electronic markets: Price premiums and buyer behavior, *MIS Quarterly: Management Information Systems* 26(3): 243–268.

Ba, S., Whinston, A. B. and Zhang, H. (2003). Building trust in online auction markets through an economic incentive mechanism, *Decision Support Systems* 35(3): 273–286.

Beckman, C. M., Haunschild, P. R. and Phillips, D. J. (2004). Friends or strangers? Firm-specific uncertainty, market uncertainty, and network partner selection, *Organization Science* 15(3).

Beese, J., Haki, M. K., Aier, S. and Winter, R. (2019). Simulation-Based Research in Information Systems: Epistemic Implications and a Review of the Status Quo, *Business and Information Systems Engineering* 61(4): 503–521. Retrieved from https://link.springer.com/article/10.1007/s12599-018-0529-1

Berger, J. and Iyengar, R. (2013). Communication channels and word of mouth: How the medium shapes the message, *Journal of Consumer Research* 40(3): 567–579. Retrieved from https://academic.oup.com/jcr/article/40/3/567/2379777

Bolton, G. E., Katok, E. and Ockenfels, A. (2004). How Effective Are Electronic Reputation Mechanisms? An Experimental Investigation, *Management Science* 50(11): 1587–1602. Retrieved from https://pubsonline.informs.org/doi/abs/10.1287/mnsc.1030.0199

Borgatti, S. P. and Foster, P. C. (2003). The network paradigm in organizational research: A review and typology, *Journal of Management* 29(6): 991–1013.

Breidbach, C. F. and Maglio, P. P. (2016). Technology-enabled value co-creation: An empirical analysis of actors, resources, and practices, *Industrial Marketing Management* 56: 73–85.

Bulut, Z. A. and Karabulut, A. N. (2018). Examining the role of two aspects of eWOM in online repurchase intention: An integrated trust–loyalty perspective, *Journal of Consumer Behaviour* 17(4): 407–417. Retrieved from https://onlinelibrary.wiley.com/doi/full/10.1002/cb.1721

Cao, Z. and Lumineau, F. (2015). Revisiting the interplay between contractual and relational governance: A qualitative and meta-analytic investigation, *Journal of Operations Management* 33–34: 15–42.

Capaldo, A. (2014). Network governance: A cross-level study of social mechanisms, knowledge benefits, and strategic outcomes in joint-design alliances, *Industrial Marketing Management* 43(4): 685–703.

Carson, D., Gilmore, A., Perry, C. and Gronhaug, K. (2001). *Qualitative Marketing Research*, SAGE. Retrieved from https://books.google.co.uk/books?hl=en&lr=&id=L8nSK5QEeGEC&oi=fnd&pg=PP1&ots=I1kpoDkvoK&sig=LIZxSwegStd26DUGuAy1IJM-M3k&redir_esc=y#v=onepage&q&f=false

Carson, S. J., Madhok, A. and Tao, W. (2006). Uncertainty, opportunism, and governance: The effects of volatility and ambiguity on formal and relational contracting, *Academy of Management Journal* 49(5): 1058–1077.

Chakravarty, A., Kumar, A. and Grewal, R. (2014). Customer Orientation Structure for Internet-Based Business-to-Business Platform Firms:, *Journal of Marketing* 78(5): 1–23. Retrieved from https://journals.sagepub.com/doi/full/10.1509/jm.12.0442

Chang, R. M., Oh, W., Pinsonneault, A. and Kwon, D. (2010). A Network Perspective of Digital Competition in Online Advertising Industries: A Simulation-Based Approach, *Information Systems Research* 21(3): 571–593. Retrieved from https://pubsonline.informs.org/doi/abs/10.1287/isre.1100.0302

Chatterjee, P. (2001). Online Reviews: Do Consumers Use Them?, *Advances in Consumer Research* (28): 129–133. Retrieved from https://linkinghub.elsevier.com/retrieve/pii/B9780750672931500093

Chien, S. H., Chen, Y. H. and Hsu, C. Y. (2012). Exploring the impact of trust and relational embeddedness in e-marketplaces: An empirical study in Taiwan, *Industrial Marketing Management* 41(3): 460–468.

Collis, J. and Hussey, R. (2009). Business Research A Practical Guide for Undergraduate and Postgraduate Students 3rd edition. Retrieved from www.palgrave.com

Davenport, T., Guha, A., Grewal, D. and Bressgott, T. (2020). How artificial intelligence will change the future of marketing, *Journal of the Academy of Marketing Science* 48(1): 24–42. Retrieved from https://link.springer.com/article/10.1007/s11747-019-00696-0

Davis, J. P., Eisenhardt, K. M. and Bingham, C. B. (2007). Developing theory through simulation methods, *Academy of Management Review* 32(2): 480–499.

Deeds, D. L. and Hill, C. W. L. (1999). An examination of opportunistic action within research alliances: Evidence from the biotechnology industry, *Journal of Business Venturing* 14(2): 141–163.

Dibbern, J., Goles, T., Hirschheim, R. and Jayatilaka, B. (2004). Information Systems Outsourcing: A Survey and Analysis of the Literature, *Data Base for Advances in Information Systems* 35(4): 6–102. Retrieved from https://dl.acm.org/doi/10.1145/1035233.1035236

Dikow, H., Hasan, O., Kosch, H., Brunie, L., Sornin, R., Dikow, H., Hasan, O., Brunie, · L, Brunie, L. and Kosch, H. (2015). Improving the accuracy of Business-to-Business (B2B) reputation systems through rater expertise prediction, *Computing* 97: 29–49.

DiMaggio, P. and Louch, H. (1998). Socially embedded consumer transactions: for what kinds of purchases do people most often use networks?, *American Sociological Review* 63(5): 619–637.

Druckenmiller, D. A. and Acar, W. (2009). An Agent-Based Collaborative Approach to Graphing Causal Maps for Situation Formulation, *Journal of the Association for Information Systems* 10(3): 3. Retrieved from https://aisel.aisnet.org/jais/vol10/iss3/3

Eisenhardt, K. M. (1989). Agency Theory: An Assessment and Review, *Academy of Management Review* 14(1): 57–74.

Eldabi, T., Irani, Z., Paul, R. J. and Love, P. E. d. (2002). Quantitative and qualitative decision□making methods in simulation modelling, *Management Decision* 40(1): 64–73.

Folta, T. B. (1998). Governance and uncertainty: the trade-off between administrative control and commitment, *Strategic Management Journal* 19(11): 1007–1028.

Frank, U., Strecker, S., Fettke, P., Vom Brocke, J., Becker, J. and Sinz, E. (2014). The research field ‘modeling business information systems’: Current challenges and elements of a future research agenda, *Business and Information Systems Engineering* 6(1): 39–43. Retrieved from https://link.springer.com/article/10.1007/s12599-013-0301-5

Gargiulo, M. and Benassi, M. (2000). Trapped in Your Own Net? Network Cohesion, Structural Holes, and the Adaptation of Social Capital, *Organization Science* 11(2): 183–196. Retrieved from https://pubsonline.informs.org/doi/abs/10.1287/orsc.11.2.183.12514

Gefen, D. and Carmel, E. (2008). Is the world really flat? A look at offshoring at an online programming marketplace, *MIS Quarterly: Management Information Systems* 32(2): 367–384.

Gilbert, N. and Terna, P. (2000). How to Build and Use Agent-Based Models in Social Science, *Mind & Society* 1: 57–72.

Gilsing, V., Vanhaverbeke, W. and Pieters, M. (2014a). Mind the gap. Balancing alliance network and technology portfolios during periods of technological uncertainty., *Technological Forecasting and Social Change* 81(1): 351–362.

Gilsing, V., Vanhaverbeke, W. and Pieters, M. (2014b). Mind the gap: Balancing alliance network and technology portfolios during periods of technological uncertainty, *Technological Forecasting and Social Change* 81(1): 351–362.

Glaser, B. G. and Strauss, A. L. (2017). Discovery of grounded theory: Strategies for qualitative research, *Discovery of Grounded Theory: Strategies for Qualitative Research* : 1–271. Retrieved from https://www.taylorfrancis.com/books/mono/10.4324/9780203793206/discovery-grounded-theory-barney-glaser-anselm-strauss

Goo, J., Kishore, R., Nam, K., Rao, H. R. and Song, Y. (2007a). An investigation of factors that influence the duration of IT outsourcing relationships, *Decision Support Systems* 42(4): 2107–2125.

Goo, J., Kishore, R., Nam, K., Rao, H. R. and Song, Y. (2007b). An investigation of factors that influence the duration of IT outsourcing relationships, *Decision Support Systems* 42(4): 2107–2125.

Goo, J. and Nam, K. (2007). Contract as a source of trust - Commitment in successful IT outsourcing relationship: An empirical study, In *Proceedings of the Annual Hawaii International Conference on System Sciences*.

Gopal, A. and Koka, B. R. (2012). The asymmetric benefits of relational flexibility: Evidence from software development outsourcing, *MIS Quarterly: Management Information Systems* 36(2): 553–576.

Granovetter, M. (1985). Economic Action and Social Structure: The Problem of Embeddedness, *American Journal of Sociology* 91(3): 481–510.

Granovetter, M. (1992). Economic Institutions as Social Constructions: A Framework for Analysis, *Acta Sociologica* 35(1): 3–11. Retrieved from http://journals.sagepub.com/doi/10.1177/000169939203500101

Gulati, R. (1995). Social Structure and Alliance Formation Patterns: A Longitudinal Analysis, *Administrative Science Quarterly* 40(4): 619.

Guo, W., Straub, D., Zhang, P. and Cai, Z. (2021). How trust leads to commitment on microsourcing platforms: Unraveling the effects of governance and third-party mechanisms on triadic microsourcing relationships, *MIS Quarterly: Management Information Systems* 45(3): 1309–1348.

Hahn, J. and Lee, G. (2021). The Complex Effects of Cross-Domain Knowledge on IS Development: A Simulation-Based Theory Development, *MISQ* 45(4). Retrieved from https://papers.ssrn.com/abstract=2563009

Haki, K., Beese, J., Aier, S. and Winter, R. (2020). The evolution of information systems architecture: An agent-based simulation model, *MIS Quarterly: Management Information Systems* 44(1): 155–184.

Handley, S. M. and Benton, W. C. (2012). The influence of exchange hazards and power on opportunism in outsourcing relationships, *Journal of Operations Management* 30(1–2): 55–68.

Harrison, J. R., Lin, Z., Carroll, G. R. and Carley, K. M. (2007). Simulation modeling in organizational and management research, *Academy of Management Review* 32(4): 1229–1245.

Hauser, F., Hautz, J., Hutter, K. and Füller, J. (2017). Firestorms: Modeling conflict diffusion and management strategies in online communities, *The Journal of Strategic Information Systems* 26(4): 285–321.

Hawkins, T. G., Wittmann, C. M. and Beyerlein, M. M. (2008). Antecedents and consequences of opportunism in buyer-supplier relations: Research synthesis and new frontiers, *Industrial Marketing Management*.

Hess, M. and Ricart, J. E. (2003). MANAGING CUSTOMER SWITCHING COSTS A Framework for Competing in the Networked Environment, *Management Research* 1(1): 93–110.

Hill, C. W. L. (1990). Cooperation, Opportunism, and the Invisible Hand: Implications for Transaction Cost Theory, *Academy of Management Review* 15(3): 500–513.

Hong, Y. and Pavlou, P. A. (2017). On Buyer Selection of Service Providers in Online Outsourcing Platforms for IT Services, *Information Systems Research* 28(3): 547–562. Retrieved from https://pubsonline.informs.org/doi/abs/10.1287/isre.2017.0709

Hudson, L. A. and Ozanne, J. L. (1988). Alternative Ways of Seeking Knowledge in Consumer Research, *Journal of Consumer Research* 14(4): 508. Retrieved from /record/1988-28241-001

Jiju, A. (2014). Design of Experiment for engineer and scientists, *Elsevier*. Retrieved from https://www.elsevier.com/books/design-of-experiments-for-engineers-and-scientists/antony/978-0-08-099417-8

Kandori, M. (1992). Social Norms and Community Enforcement, *The Review of Economic Studies* 59(1): 63. Retrieved from https://academic.oup.com/restud/article-lookup/doi/10.2307/2297925

Kang, T. H., Chien, W. and Shen, S. S. (2016). The study for selecting the cloud service consignment performance in group decision of shared inventory resource in small-sized electronic industry, In *2016 International Conference on Applied System Innovation, IEEE ICASI 2016*, Institute of Electrical and Electronics Engineers Inc.

Keuk, S. C., Paradi-Guilford, C., Fayomi, T., Iamizumi, S. and Ipeirotis, P. (2015, June). The Global Opportunity in Online Outsourcing, *World Bank*. Retrieved October 18, 2022, from https://openknowledge.worldbank.org/bitstream/handle/10986/22284/The0global0opp0n0online0outsourcing.pdf?sequence=1&isAllowed=y

Kim, S. and Chung, Y. S. (2003, June). Critical success factors for is outsourcing implementation from an interorganizational relationship perspective, *Journal of Computer Information Systems*.

Koufaris, M. and Hampton-Sosa, W. (2004). The development of initial trust in an online company by new customers, *Information & Management* 41(3): 377–397.

Lacity, M. C., Khan, S., Yan, A. and Willcocks, L. P. (2010). A review of the IT outsourcing empirical literature and future research directions, *Journal of Information Technology* 25(4): 395–433.

Lee, J., Lee, J. and Lee, H. (2003). Exploration and exploitation in the presence of network externalities, *Management Science* 49(4): 553–570. Retrieved from https://pubsonline.informs.org/doi/abs/10.1287/mnsc.49.4.553.14417

Lee, J. N. and Kim, Y. G. (2005). Understanding outsourcing partnership: A comparison of three theoretical perspectives, *IEEE Transactions on Engineering Management* 52(1): 43–58.

Li, N., Li, X., Shen, Y., Bi, Z. and Sun, M. (2015). Risk assessment model based on multi-agent systems for complex product design, *Information Systems Frontiers* 17(2): 363–385. Retrieved from https://link.springer.com/article/10.1007/s10796-013-9452-7

Li, Y., Chen, K., Collignon, S. and Ivanov, D. (2021). Ripple effect in the supply chain network: Forward and backward disruption propagation, network health and firm vulnerability, *European Journal of Operational Research* 291(3): 1117–1131.

Liang, C., Hong, Y. and Gu, B. (2016). Effects of IT-Enabled Monitoring Systems in Online Labor Markets, In *Proceedings of International Conference on Information Systems*, Dublin. Retrieved from https://papers.ssrn.com/abstract=2843944

Lin, F. R., Sung, Y. W. and Lo, Y. P. (2005). Effects of Trust Mechanisms on Supply-Chain Performance: A Multi-Agent Simulation Study, *International Journal of Electronic Commerce* 9(4): 9–112. Retrieved from https://www.tandfonline.com/doi/abs/10.1080/10864415.2003.11044342

Lin, N. (1999). SOCIAL NETWORKS AND STATUS ATTAINMENT, *Annual Review of Sociology* 25. Retrieved from https://www.annualreviews.org/doi/abs/10.1146/annurev.soc.25.1.467

Lu, B., Zeng, Q. and Fan, W. (2016). Examining macro-sources of institution-based trust in social commerce marketplaces: An empirical study, *Electronic Commerce Research and Applications* 20: 116–131.

Lumineau, F. and Henderson, J. E. (2012). The influence of relational experience and contractual governance on the negotiation strategy in buyer-supplier disputes, *Journal of Operations Management* 30(5): 382–395.

Luo, Y. (2007). Are joint venture partners more opportunistic in a more volatile environment?, *Strategic Management Journal* 28(1): 39–60. Retrieved from http://doi.wiley.com/10.1002/smj.564

Macneil, I. R. (1980). Power, Contract, and the Economic Model, *Journal of Economic Issues* 14(4). Retrieved from https://www.tandfonline.com/doi/abs/10.1080/00213624.1980.11503791

McKnight, D. H., Lankton, N. K., Nicolaou, A. and Price, J. (2017). Distinguishing the effects of B2B information quality, system quality, and service outcome quality on trust and distrust, *The Journal of Strategic Information Systems* 26(2): 118–141.

Meuleman, M., Lockett, A., Manigart, S. and Wright, M. (2010). Partner selection decisions in interfirm collaborations: The paradox of relational embeddedness, *Journal of Management Studies* 47(6): 995–1019. Retrieved from http://doi.wiley.com/10.1111/j.1467-6486.2009.00897.x

Moran, P. (2005, December 1). Structural vs. relational embeddedness: Social capital and managerial performance, *Strategic Management Journal*. Retrieved from https://onlinelibrary.wiley.com/doi/full/10.1002/smj.486

Nooteboom, B. (2016). Trust, Opportunism and Governance: A Process and Control Model:, *Organization Studies* 17(6): 985–1010. Retrieved from https://journals.sagepub.com/doi/abs/10.1177/017084069601700605

Nosko, C. and Tadelis, S. (2015a). The Limits of Reputation in Platform Markets: An Empirical Analysis and Field Experiment, *Natinal Bureau of Economic Research*. Retrieved from https://www.nber.org/papers/w20830

Nosko, C. and Tadelis, S. (2015b). The Limits of Reputation in Platform Markets: An Empirical Analysis and Field Experiment, *NBER*. Retrieved from https://www.nber.org/papers/w20830

Nunlee, M. P. (2005). The control of intra-channel opportunism through the use of inter-channel communication, *Industrial Marketing Management* 34(5): 515–525.

Oh, J. (2013). Relational versus structural embeddedness : the roles of uncertainty in information technology outsourcing. Retrieved from http://bura.brunel.ac.uk/handle/2438/7641

Oh, W., Moon, J. Y., Hahn, J. and Kim, T. (2016). Research Note—Leader Influence on Sustained Participation in Online Collaborative Work Communities: A Simulation-Based Approach, *Information Systems Reseach* 27(2): 383–402. Retrieved from https://pubsonline.informs.org/doi/abs/10.1287/isre.2016.0632

Oinonen, M., Ritala, P., Jalkala, A. and Blomqvist, K. (2018). In search of paradox management capability in supplier–customer co-development, *Industrial Marketing Management* 74: 102–114.

Parkhe, A. (1993). Strategic Alliance Structuring: A Game Theoretic and Transaction Cost Examination of Interfirm Cooperation, *Academy of Management Journal* 36(4): 794–829. Retrieved from https://journals.aom.org/doi/abs/10.5465/256759

Pathak, B., Ashok, M. and Tan, Y. L. (2020). Value co-destruction: Exploring the role of actors' opportunism in the B2B context, *International Journal of Information Management* 52: 102093.

Pavlou, P. A. (2002). Institution-based trust in interorganizational exchange relationships: the role of online B2B marketplaces on trust formation, *The Journal of Strategic Information Systems* 11(3–4): 215–243.

Pavlou, P. A. and Gefen, D. (2004). Building Effective Online Marketplaces with Institution-Based Trust, *Information Systems Research* 15(1): 37–59. Retrieved from https://pubsonline.informs.org/doi/abs/10.1287/isre.1040.0015

Perry, M. L., Sengupta, S. and Krapfel, R. (2004). Effectiveness of horizontal strategic alliances in technologically uncertain environments: Are trust and commitment enough?, *Journal of Business Research* 57(9): 951–956.

Poppo, L. and Zenger, T. (2002). Do formal contracts and relational governance function as substitutes or complements?, *Strategic Management Journal* 23(8): 707–725. Retrieved from http://doi.wiley.com/10.1002/smj.249

Poppo, L., Zhou, K. Z. and Ryu, S. (2008). Alternative Origins to Interorganizational Trust: An Interdependence Perspective on the Shadow of the Past and the Shadow of the Future, *Ogranization Science* 19(1): 39–55. Retrieved from https://pubsonline.informs.org/doi/abs/10.1287/orsc.1070.0281

Ravindran, K., Susarla, A., Mani, D. and Gurbaxani, V. (2015). Social capital and contract duration in buyer-supplier networks for information technology outsourcing, *Information Systems Research* 26(2): 379–397.

Rivkin, J. W. and Siggelkow, N. (2007). Patterned Interactions in Complex Systems: Implications for Exploration, *Management Science* 53(7): 1068–1085. Retrieved from https://pubsonline.informs.org/doi/abs/10.1287/mnsc.1060.0626

Rohm, A. J., Kashyap, V., Brashear, T. G. and Milne, G. R. (2004). The use of online marketplaces for competitive advantage: A Latin American perspective, *Journal of Business and Industrial Marketing* 19(6): 372–385.

Rowley, T., Behrens, D. and Krackhardt, D. (2000). Redundant governance structures: an analysis of structural and relational embeddedness in the steel and semiconductor industries, *Strategic Management Journal* 21(3): 369–386.

SAP Ariba network. (2023). SAP Ariba network. Retrieved January 30, 2023, from https://www.ariba.com/solutions

Shuang, Y. (2013). Effects of information quality and source credibility on EWOM adoption in context of virtual community, *International Conference on Management Science and Engineering - Annual Conference Proceedings* : 194–200.

Son, B. G., Kocabasoglu-Hillmer, C. and Roden, S. (2016). A dyadic perspective on retailer-supplier relationships through the lens of social capital, *International Journal of Production Economics* 178: 120–131.

Tripsas, M., Schrader, S. and Sobrero, M. (1995). Discouraging opportunistic behavior in collaborative R & D: A new role for government, *Research Policy* 24(3): 367–389.

Uzzi, B. (1996). The sources and consequences of embeddedness for the economic performance of organizations: The network effect, *American Sociological Review* 61(4): 674–698.

Uzzi, B. (1997). Social structure and competition in interfirm networks: The paradox of embeddedness, *Administrative Science Quarterly* 42(1): 35–67.

Van Alstyne, M. W. and Parker, G. G. (2016, April). Pipelines, Platforms, and the New Rules of Strategy, *Harvard Business Review*. Retrieved from https://hbr.org/2016/04/pipelines-platforms-and-the-new-rules-of-strategy

Wang, E. T. G. (2002). Transaction attributes and software outsourcing success: an empirical investigation of transaction cost theory, *Information Systems Journal* 12(2): 153–181. Retrieved from https://onlinelibrary.wiley.com/doi/full/10.1046/j.1365-2575.2002.00120.x

Wathne, K. H. and Heide, J. B. (2000). Opportunism in Interfirm Relationships: Forms, Outcomes, and Solutions, *Journal of Marketing* 64(4): 36–51. Retrieved from http://journals.sagepub.com/doi/10.1509/jmkg.64.4.36.18070

Wei, R., Wang, X. and Chang, Y. (2021). The effects of platform governance mechanisms on customer participation in supplier new product development, *Journal of Business Research* 137: 475–487.

Weick, K. E. (1989). Theory Construction as Disciplined Imagination, *Academy of Management Review* 14(4): 516–531. Retrieved from https://journals.aom.org/doi/abs/10.5465/amr.1989.4308376

Wiengarten, F., Humphreys, P., Cao, G., Fynes, B. and McKittrick, A. (2010). Collaborative supply chain practices and performance: Exploring the key role of information quality, *Supply Chain Management* 15(6): 463–473.

Williamson, O. E. (1975). Markets and Hierarchies: Analysis and Antitrust Implications: A Study in the Economics of Internal Organization. Retrieved from https://papers.ssrn.com/abstract=1496220

Yamakawa, Y., Yang, H. and Lin, Z. (2011). Exploration versus exploitation in alliance portfolio: Performance implications of organizational, strategic, and environmental fit, *Research Policy* 40(2): 287–296.

Yoon, Y. L., Yoon, Y., Nam, H. and Choi, J. (2021). Buyer-supplier matching in online B2B marketplace: An empirical study of small- and medium-sized enterprises (SMEs), *Industrial Marketing Management* 93: 90–100.

Za, S., Spagnoletti, P., Winter, R., Mettler, T., Za, S. ;, Spagnoletti, P. ; and Winter, R. ; (2018). Exploring Foundations for Using Simulations in IS Research, *Communications of the Association for Information Systems* 42(1): 10. Retrieved from https://aisel.aisnet.org/cais/vol42/iss1/10

Zhang, D., Zhou, L., Kehoe, J. L., Isil, & and Kilic, Y. (2016). What Online Reviewer Behaviors Really Matter? Effects of Verbal and Nonverbal Behaviors on Detection of Fake Online Reviews, *Journal of Management Information System* 33(2): 456–481. Retrieved from https://www.tandfonline.com/action/journalInformation?journalCode=mmis20

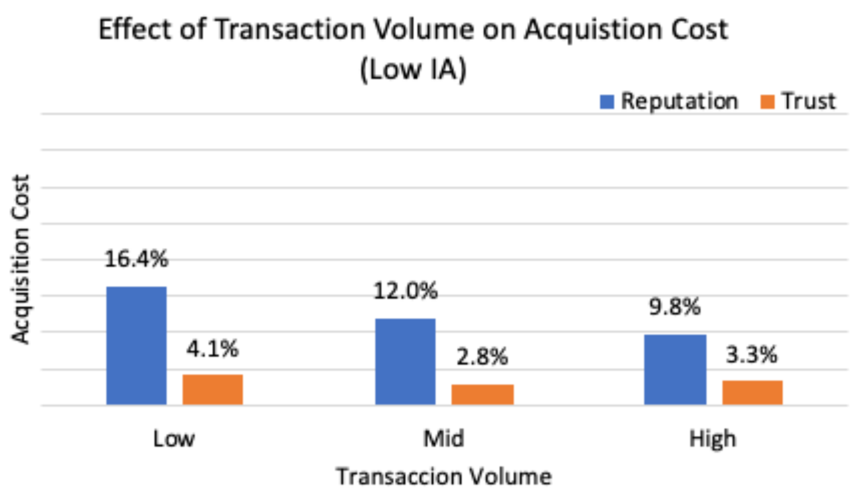
Zheng, H., Xu, B. and Lin, Z. (2019). Seller's creditworthiness in the online service market: A study from the control perspective, *Decision Support Systems* 127: 113118.

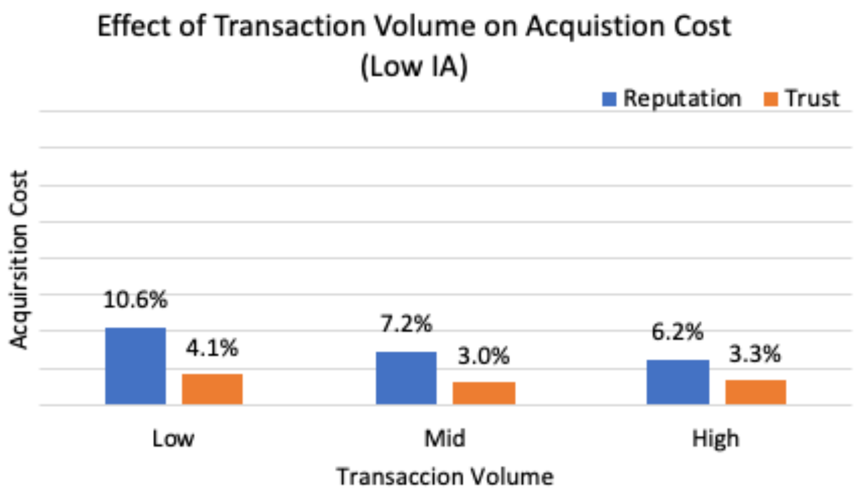
Zhou, L., Mao, H., Zhao, T., Wang, V. L., Wang, X. and Zuo, P. (2022). How B2B platform improves Buyers' performance: Insights into platform's substitution effect, *Journal of Business Research* 143: 72–80.

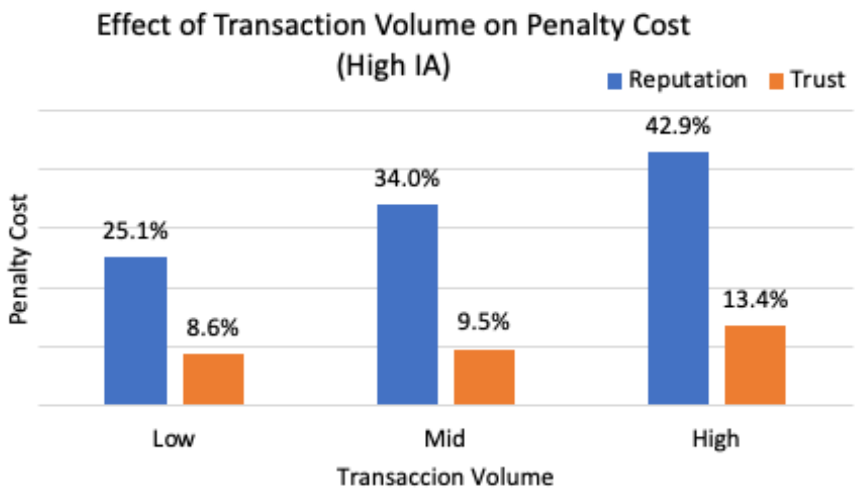
Appendix A. Simulation Results

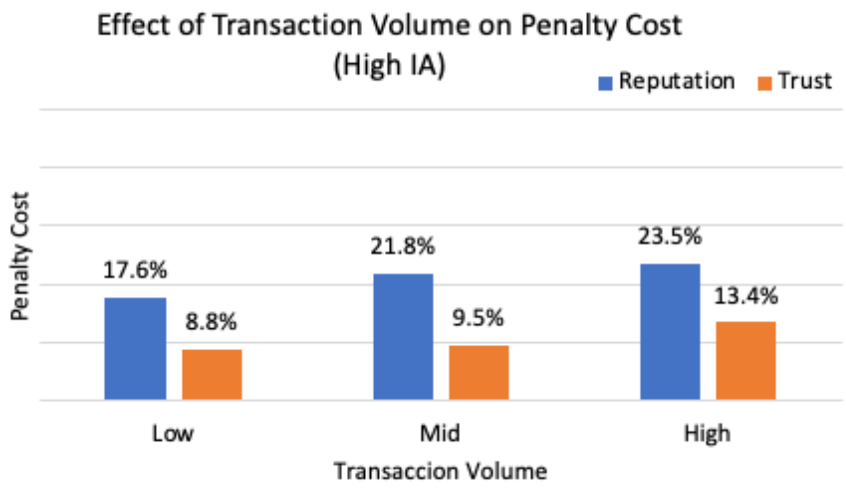
This appendix shows the simulation results of Experiment 3, 4 and 5, which were not included in Chapter 5.

A.1 Effect of Transaction Volume (extended from Chapter 5.4)






Effect of Transaction Volume on Penalty Cost
(High IA)
Reputation
Trust
Penalty Cost
25.1%
8.6%
34.0%
9.5%
42.9%
13.4%
Low
Mid
High
Transaccion Volume


Effect of Transaction Volume on Penalty Cost
(High IA)
Reputation
Trust
Penalty Cost
17.6%
8.8%
21.8%
9.5%
23.5%
13.4%
Low
Mid
High
Transaccion Volume

A.2 Simulation of Full factorial points (averaged over 100 runs)

Variables				Profitability		Ties		Opportunism		Acquisition Cost		Penalty Cost		Consortium Success	
MD	TU	IA	TV	Reput'n	Trust	Reput'n	Trust	Reput'n	Trust	Reput'n	Trust	Reput'n	Trust	Reput'n	Trust
Low	Low	Low	Low	0.848	95.2%	23.5%	16.0%	27.6%	9.0%	16.4%	4.1%	25.1%	8.6%	100.0%	100.0%
Low	Mid	Low	Low	0.771	85.1%	31.4%	25.8%	29.0%	19.2%	25.8%	14.1%	27.4%	16.2%	99.2%	97.5%
Low	High	Low	Low	0.684	71.7%	35.0%	30.8%	31.6%	24.8%	34.1%	25.0%	29.6%	21.5%	95.6%	91.4%
Mid	Low	Low	Low	0.733	85.4%	23.3%	14.8%	31.7%	19.9%	16.3%	3.8%	57.9%	36.7%	100.0%	100.0%
Mid	Mid	Low	Low	0.659	74.8%	31.4%	24.4%	32.9%	27.5%	25.8%	12.2%	60.4%	49.8%	99.4%	98.4%
Mid	High	Low	Low	0.579	62.9%	35.3%	29.9%	34.9%	32.2%	33.5%	22.6%	62.5%	55.9%	96.7%	93.6%
High	Low	Low	Low	0.564	65.3%	22.8%	13.1%	38.7%	33.6%	15.7%	3.0%	106.7%	95.2%	100.0%	100.0%
High	Mid	Low	Low	0.477	58.4%	31.2%	22.5%	40.6%	37.2%	26.1%	9.5%	112.4%	103.5%	99.7%	99.3%
High	High	Low	Low	0.428	49.1%	35.2%	28.5%	40.4%	39.4%	33.3%	19.1%	107.5%	107.1%	97.4%	96.0%
Low	Low	Mid	Low	0.887	95.1%	20.4%	16.2%	21.1%	9.3%	12.4%	4.1%	19.6%	8.6%	100.0%	100.0%
Low	Mid	Mid	Low	0.833	84.3%	28.3%	25.7%	21.2%	18.6%	20.2%	14.1%	18.4%	16.7%	99.1%	97.2%
Low	High	Mid	Low	0.749	72.6%	32.7%	30.8%	22.1%	24.3%	28.3%	25.3%	19.1%	19.8%	95.7%	91.3%
Mid	Low	Mid	Low	0.783	85.1%	20.4%	14.7%	27.0%	20.4%	12.2%	3.6%	49.4%	38.4%	100.0%	100.0%
Mid	Mid	Mid	Low	0.725	74.4%	28.3%	24.4%	26.8%	27.4%	20.3%	12.3%	48.7%	50.1%	99.0%	97.8%
Mid	High	Mid	Low	0.647	62.6%	32.9%	29.9%	28.0%	31.3%	28.1%	23.0%	50.6%	55.0%	96.0%	92.9%
High	Low	Mid	Low	0.636	66.1%	20.1%	13.2%	34.1%	33.2%	11.5%	3.3%	92.1%	92.6%	100.0%	100.0%
High	Mid	Mid	Low	0.567	57.9%	28.1%	22.4%	34.6%	36.7%	20.0%	9.6%	94.2%	102.3%	99.3%	98.7%
High	High	Mid	Low	0.48	48.9%	32.8%	28.5%	37.0%	39.1%	28.2%	18.6%	100.1%	104.9%	97.0%	95.0%
Low	Low	High	Low	0.903	94.8%	19.2%	16.3%	18.6%	9.4%	10.6%	4.1%	17.6%	8.8%	100.0%	100.0%

Low	Mid	High	Low	0.842	83.4%	26.7%	25.5%	18.9%	18.8%	17.8%	14.5%	17.0%	16.5%	98.4%	96.3%
Low	High	High	Low	0.776	71.2%	31.7%	30.5%	20.4%	24.1%	25.0%	25.5%	18.4%	20.5%	96.3%	90.2%
Mid	Low	High	Low	0.813	85.5%	19.3%	14.8%	23.8%	20.1%	10.2%	3.5%	43.5%	37.1%	100.0%	100.0%
Mid	Mid	High	Low	0.752	74.3%	26.8%	24.3%	24.2%	26.8%	17.5%	12.6%	43.4%	48.7%	98.8%	97.4%
Mid	High	High	Low	0.673	63.3%	31.7%	29.8%	26.8%	29.9%	25.6%	23.2%	48.1%	51.6%	96.4%	92.2%
High	Low	High	Low	0.65	65.8%	19.1%	13.3%	32.4%	32.9%	10.6%	3.2%	89.3%	93.2%	100.0%	100.0%
High	Mid	High	Low	0.579	59.0%	26.7%	22.6%	33.5%	35.7%	17.3%	9.8%	93.8%	97.5%	99.0%	98.4%
High	High	High	Low	0.508	49.9%	31.6%	28.7%	35.8%	38.5%	24.7%	19.1%	97.1%	102.9%	97.1%	95.2%
Low	Low	Low	Mid	0.881	96.7%	28.6%	17.6%	24.6%	6.8%	12.0%	2.8%	34.0%	9.5%	100.0%	100.0%
Low	High	Low	Mid	0.749	76.2%	43.4%	35.9%	26.9%	19.9%	24.3%	15.5%	36.1%	25.7%	94.6%	88.5%
High	Low	Low	Mid	0.615	68.9%	27.9%	14.8%	36.3%	30.7%	11.3%	2.6%	149.1%	129.2%	100.0%	100.0%
High	High	Low	Mid	0.496	54.7%	43.7%	32.9%	36.8%	36.4%	23.9%	10.9%	148.9%	144.0%	95.9%	93.8%
Low	Low	Mid	Mid	0.923	96.2%	24.6%	17.8%	17.1%	7.6%	8.6%	3.2%	23.4%	11.0%	100.0%	100.0%
Low	High	Mid	Mid	0.8	74.4%	39.5%	35.6%	18.6%	20.1%	18.3%	15.8%	24.5%	23.9%	94.2%	86.5%
High	Low	Mid	Mid	0.675	69.3%	24.3%	15.0%	31.3%	30.4%	8.4%	2.7%	129.4%	127.2%	100.0%	100.0%
High	High	Mid	Mid	0.579	55.5%	40.1%	33.1%	31.2%	35.5%	19.1%	11.5%	124.4%	140.9%	96.1%	93.4%
Low	Low	High	Mid	0.932	96.7%	23.0%	17.9%	15.3%	7.1%	7.2%	3.0%	21.8%	9.5%	100.0%	100.0%
Low	High	High	Mid	0.828	74.4%	37.6%	35.6%	15.5%	19.3%	15.6%	15.7%	20.5%	23.8%	94.9%	87.1%
High	Low	High	Mid	0.712	70.1%	22.8%	15.1%	28.0%	29.4%	7.4%	2.6%	115.1%	124.0%	100.0%	100.0%
High	High	High	Mid	0.583	54.8%	37.7%	33.1%	31.2%	34.9%	16.0%	11.1%	123.9%	135.0%	94.9%	91.8%
Low	Low	Low	High	0.898	96.5%	33.4%	19.7%	23.8%	6.9%	9.8%	3.3%	42.9%	13.4%	100.0%	100.0%
Low	High	Low	High	0.771	77.1%	49.4%	39.3%	25.9%	16.5%	18.3%	10.5%	42.9%	26.0%	92.6%	85.8%
High	Low	Low	High	0.646	70.5%	32.5%	16.6%	34.6%	29.4%	9.2%	2.6%	187.9%	164.3%	100.0%	100.0%
High	High	Low	High	0.541	57.8%	50.4%	36.3%	35.8%	34.1%	18.0%	7.3%	190.6%	177.8%	95.5%	92.3%
Low	Low	Mid	High	0.932	96.6%	28.7%	20.0%	16.5%	7.6%	7.2%	3.3%	30.4%	13.0%	100.0%	100.0%
Low	High	Mid	High	0.829	75.7%	44.9%	39.5%	16.4%	17.3%	13.7%	11.1%	27.5%	27.9%	93.8%	85.5%

High	Low	Mid	High	0.692	71.1%	28.3%	16.8%	30.2%	28.9%	7.1%	2.5%	167.1%	161.6%	100.0%	100.0%
High	High	Mid	High	0.632	58.1%	45.8%	36.4%	27.6%	33.6%	14.4%	7.7%	146.5%	169.2%	95.4%	91.9%
Low	Low	High	High	0.948	96.6%	26.4%	20.1%	12.8%	7.4%	6.2%	3.3%	23.5%	13.4%	100.0%	100.0%
Low	High	High	High	0.846	74.3%	42.3%	39.1%	15.0%	16.8%	11.3%	11.1%	25.7%	26.0%	93.8%	83.5%
High	Low	High	High	0.734	71.8%	26.3%	17.0%	26.3%	28.4%	6.0%	2.6%	145.7%	157.0%	100.0%	100.0%
High	High	High	High	0.664	58.8%	42.7%	36.6%	24.8%	32.5%	11.8%	8.0%	131.5%	167.7%	95.2%	91.4%

Appendix B. Simulation Parameters

Parameter	Description
P_sanction = 2	Period of Sanction
step = 200	Period of Simulation (round)
NumberOfPart = 100	Number of Coordinators and Suppliers in a market
Coordinator_weight = 0.5	Proportion of coordinators with reputation-based strategy (50%)
Supplier_weight = 0.5	Proportion of Opportunistic suppliers (50%)
Data_cc_profit = 0.05	Rewarding rate for coordinator, from own resource (5%)
Data_ct_profit = 0.10	Rewarding rate for coordinator, from each partner's tech resource (10%)
Data_pt_profit = 0.10	Rewarding rate for each supplier, partner's tech resource (10%)
Data_pt_def_penalty = 0.15	Rewarding/penalty rate for each supplier, the defecting resource (15%), Data_pt_def_profit = Data_pt_def_penalty
defection_option = 0.2	Rate of defection out of outsourced resource (20%)
Data.req_resources = 100	Amount of resource required for each technology
Data.cost_coeff = 80	Cost of each resource for technology supplied
AcqCost_Old = 0	Acquisition cost for an old supplier
AcqCost_New = 500	Acquisition cost for a new supplier
numPart = 4	Max number of suppliers in a consortium

Appendix C. Results of Sensitivity Analysis

C.1 Network dimension (ND)

Parameter, simulations were carried out with *NumberOfPart* of 200, 100, 50.

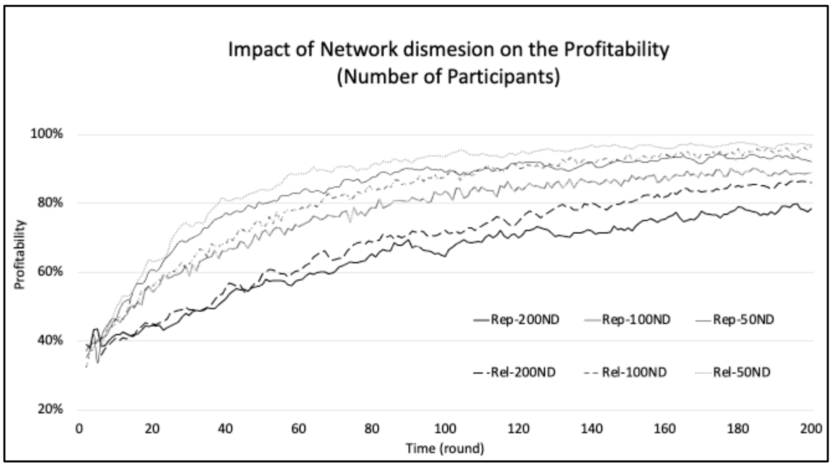


Figure C-1. Impact of network dimension on the profitability (sensitivity analysis).

Rep-100ND and Rep-100ND" represent that there are 100 buyers and 100 suppliers in the market, indicating the overall network dimension. In the base model, we used 100. Further simulations are conducted by changing the number of participants to 50 and 200, and the results are presented in Figure C-1. Similar to the results of the base model, the performance difference between the two strategy groups remained relatively consistent.

C.2 Acquisition cost (AC)

Parameter, simulations were carried out with *AcqCost_New* of 750, 500, 250.

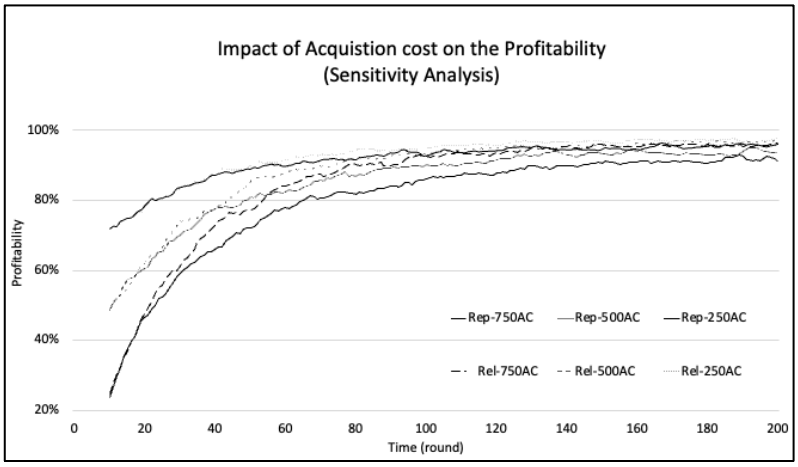


Figure C-2. Impact of Acquisition cost on the profitability (sensitivity analysis).

Rep-500AC and Rep-500AC represent the acquisition costs incurred while seeking, evaluating, and contracting with partners who have not previously worked together in the market. In the base model, a value of 500 was used. Further simulations are conducted by changing the acquisition cost to 250 and 750, and the results are presented in Figure C-2. Similar to the results of the base model, the performance difference between the two strategy groups remained relatively consistent.

C.3 Penalty Rate (PR)

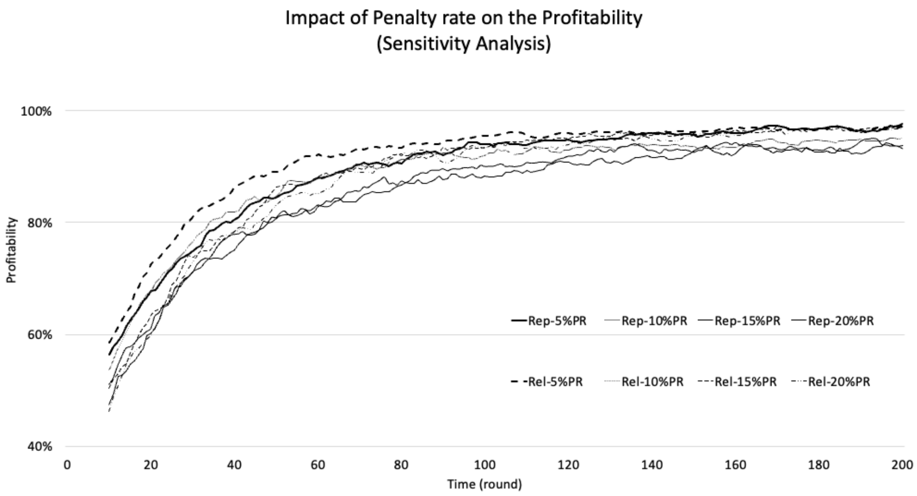


Figure C-3. Impact of Penalty Rate on the profitability

In Figure C-3, Rep-15%PR and Rep-15%PR represent the penalty intensity in the market, indicating the extent to which buyers incur losses when the project quality is compromised due to the supplier's opportunism (calculated by multiplying the penalty rate by the resources exploited by the supplier, which goes undetected). In the base model, a value of 15% was used. When varying the Penalty Rate to 5%, 10%, 15%, and 20%, the results indicated that, except for the 55% case (in bold lines, which the profitability of the two merges in the long term), relational-based selection consistently outperformed the base model, similar to the base-model results.

Appendix D. Source Codes by Simulation Stages

D.1 Bidding stage – partner-selection routine

```
for rt=1:length(req_tech_indx)
      cand_supp=find(Tech_Map(req_tech_indx(rt),:) > 0
      temp_b=[];
      no_cs=length(cand_supp);

        for i=1:(no_cs-1)
                 temp_a=randsample(cand_supp,1);
                 temp_b=[temp_b temp_a];
                 cand_supp(cand_supp==temp_a)=[];
        end

        cand_supp=[temp_b cand_supp];

        if  Part_Map(ActCoord_ID(na),3)==1

old_partners=find(Relation_Map(Act_Crd.act_crd_indx(na),:)>0);

        if length(old_partners) > rc_pool_size
            common_sup=intersect(cand_supp, old_partners);
            cand_supp=common_sup;
            NoPartnersAfterRCPoolSize=NoPartnersAfterRCPoolSize+1
            ;
           end
        end

        if  Part_Map(ActCoord_ID(na),3)==0
             P_sanction=N_nc;
        elseif Part_Map(ActCoord_ID(na),3)==1
             P_sanction=N_rc;
        else
             P_sanction=N_sc;
        end

        detected_partners=[];
        detected_temp=[];
        bf_Nsanc_candidate=cand_supp;

       if rand > gamma_ni*NET_INEFF
            if ( P_sanction > 0 )
                if  ( t > P_sanction )
                     for k=(t-1):(-1):(t-P_sanction)
```

```
                        detected_temp=find(DP(:,k))';
              detected_partners=[detected_partners,
detected_temp];
                    end
               else
                   for k=(t-1):(-1):1
                        detected_temp=find(DP(:,k))';
              detected_partners=[detected_partners,
detected_temp];
                    end
               end

                if (~isempty(detected_partners) &&
P_sanction==0)
                     detected_partners;
                end

                if ~isempty(detected_partners)
            cand_supp=setdiff(cand_supp, detected_partners);
                end
           end
       end

        if ~ isempty(cand_supp)
            reward2sup=zeros(length(cand_supp),1);
            cum_profit=zeros(length(cand_supp),1);
            num_ties=zeros(length(cand_supp),1);
            mnt_cost=zeros(length(cand_supp),1);
            obj_cost=zeros(length(cand_supp),1);
            r_trust=zeros(length(cand_supp),1);
            s_trust=zeros(length(cand_supp),1);
            candidate_rank=zeros(length(cand_supp),4);

            for cs=1:length(cand_supp)

reward2sup(cs)=BO(na).prof_mar*sum(Cost_Prt(:,cand_supp(cs)))*BO
(na).Techrequired(rt);

cum_profit(cs)=Trust_Map(ActCoord_ID(na),cand_supp(cs));

num_ties(cs)=sum(Relation_Map(:,cand_supp(cs)));
                 if S_TRUST_CPROFIT==1

s_trust(cs)=sum(CProfit_Map(:,cand_supp(cs)));
                 else
                     temp_ties=num_ties(cs);
                     if num_ties(cs) ~= 0
```

```
                        s_trust(cs)=temp_ties+NET_INEFF*randi([-
temp_ties,temp_ties],1);
                     else
                        s_trust(cs)=temp_ties ;
                     end
                 end
                 r_trust(cs)=cum_profit(cs);
                if
Relation_Map(ActCoord_ID(na),cand_supp(cs))==1
                    mnt_cost(cs)=AccCost_Old;
                else
                    mnt_cost(cs)=AccCost_New;
                end
            end
            cost_rank=floor(tiedrank(reward2sup));
            old_rank=floor(tiedrank(mnt_cost));

            if Part_Map(ActCoord_ID(na),3)==1
                if t > RC_PeriodWarmingUp
                    trust_rank=max(floor(tiedrank(r_trust)))+1-
floor(tiedrank(r_trust));
                    obj_rank=floor(tiedrank(w_c*cost_rank
+w_o*old_rank+w_t*trust_rank));
                else
                    obj_rank=floor(tiedrank(w_c*cost_rank
+w_o*old_rank ));
                end
                mnt_cost(cs)=mnt_cost(cs)+contcost_rc;

            elseif Part_Map(ActCoord_ID(na),3)==2
                if t > SC_PeriodWarmingUp
                    trust_rank=max(floor(tiedrank(s_trust)))+1-
floor(tiedrank(s_trust));
                    obj_rank=floor(tiedrank(w_c*cost_rank
+w_o*old_rank+w_t*trust_rank));

                else

obj_rank=floor(tiedrank(w_c*cost_rank+w_o*old_rank));
                end
                mnt_cost(cs)=mnt_cost(cs)+contcost_sc;
            else

obj_rank=floor(tiedrank(w_c*cost_rank+w_o*old_rank));
                mnt_cost(cs)=mnt_cost(cs)+contcost_sc;
            end
```

```
            [val,j]=min(obj_rank);

            if (val==1 && sum (obj_rank==1)==1)
                j=j;
            else
                ind=[1:length(obj_rank)]';
                ind_obj=[ind obj_rank];
                j_list=[];
                for i=1:length(obj_rank)
                    if (ind_obj(i,2)==val)
                        j_list=[j_list i];
                    end
                end
                j=randsample(j_list,1);
            end
            cand_supp(j);
            num_part(cand_supp(j))=num_part(cand_supp(j))+1;
            BO(na).SP(rt,1)=cand_supp(j);

BO(na).OfferedResource(rt,1)=BO(na).Techrequired(rt);
            BO(na).mnt_cost(rt,1)=mnt_cost(j);
            BO(na).r_trust(rt,1)=r_trust(j);
            BO(na).s_trust(rt,1)=s_trust(j);
            end
```

D.2 Implementation Stage – opportunism and detection model

```
for na=1:Act_Crd.active_coord
    defect=zeros(length(BO(na).SP),5);
    zz=CProfit_Map(BO(na).coord,:)>0;

    if all(BO(na).SP)
        for sp=1:length(BO(na).SP)
             if Relation_Map(BO(na).coord,BO(na).SP(sp))==1
                    defect(sp,1)=defect_old;
             if  Part_Map(ActCoord_ID(na),3)==

rc_AccCost_Old=rc_AccCost_Old+BO(na).mnt_cost(sp,1);

              elseif Part_Map(ActCoord_ID(na),3)==2

sc_AccCost_Old=sc_AccCost_Old+BO(na).mnt_cost(sp,1);

              end
```

```
              else
                    defect(sp,1)=defect_new;
              if  Part_Map(ActCoord_ID(na),3)==1
                    rc_mntcost_new=
rc_mntcost_new+BO(na).mnt_cost(sp,1);

              elseif Part_Map(ActCoord_ID(na),3)==2

sc_mntcost_new=sc_mntcost_new+BO(na).mnt_cost(sp,1);
              end
              end

                if (BO(na).SP(sp) <= 50)    % OP

BO(na).mnt_cost(sp,1)=BO(na).mnt_cost(sp,1)+mntcost_op;

                if  Part_Map(ActCoord_ID(na),3)==1
                        rc_mntcost_op=rc_mntcost_op+mntcost_op;

                elseif Part_Map(ActCoord_ID(na),3)==2
                        sc_mntcost_op=sc_mntcost_op+mntcost_op;
                else
                        nc_mntcost_op=nc_mntcost_op+mntcost_op;
                end

                else

BO(na).mnt_cost(sp,1)=BO(na).mnt_cost(sp,1)+mntcost_cp;
                end
                if Part_Map(BO(na).coord,3)==1
                      defect(sp,2)=defect_rc;
                      mp=Trust_Map(BO(na).coord,BO(na).SP(sp));

                 if mp >= mean(Trust_Map(BO(na).coord,zz))
                            defect(sp,3)=defect_ltr;
                  else
                            defect(sp,3)=defect_htr;
                  end
                else
                        defect(sp,2)=defect_sc;


nc=Relation_Map( BO(na).coord,BO(na).SP(sp));
                 if nc >= mean(sum(Relation_Map))
                            defect(sp,3)=defect_ltr;
                  else
```

```
                    defect(sp,3)=defect_htr;
          end
        end

        if  Part_Map(BO(na).SP(sp),1)==1
            cp=BO(na).coord;
            pp=BO(na).SP(sp);

            switch CdStrategy
                case 0
                    defect(sp,5)=defect_op;
                case 1
                    if Part_Map(ActCoord_ID(na),3)==0
                        defect(sp,5)=defect_op;
                    else

defect(sp,5)=opportunism(RTrust_max,defect_op,BO(na).r_trust(sp));
                    end
                case 2
                    if Part_Map(ActCoord_ID(na),3)==0
                        defect(sp,5)=defect_op;
                    else

defect(sp,5)=opportunism(STrust_max,defect_op,BO(na).s_trust(sp));
                    end
                case 3
                     if Part_Map(ActCoord_ID(na),3)==1

defect(sp,5)=opportunism(RTrust_max,defect_op,BO(na).r_trust(sp));
                     elseif
Part_Map(ActCoord_ID(na),3)==2

defect(sp,5)=opportunism(STrust_max,defect_op,BO(na).s_trust(sp));
                     end

                    end
                case 4

defect(sp,5)=opportunism(RTrust_max,defect_op,BO(na).r_trust(sp));

                case 5

defect(sp,5)=opportunism(STrust_max,defect_op,BO(na).s_trust(sp));

            end % end of switch loop
       else
            defect(sp,5)=defect_cp;
```

```
                end
                defect_rate=defect(sp,5);
                BO(na).DefectR(sp,1)=defect_rate;
BO(na).Defect(sp,1)=BO(na).OfferedResource(sp,1)*defect_rate;
BO(na).NetResource(sp,1)=BO(na).OfferedResource(sp,1)-
BO(na).Defect(sp,1);

                 if rand <= DETECT_PROB

                 if (BO(na).Defect(sp,1) > 0)
                        BO(na).Detected(sp,1)=1;

DP(BO(na).SP(sp),t)=DP(BO(na).SP(sp),t)+1;
                   else
                        BO(na).Detected(sp,1)=0;
                   end
                else
                    BO(na).Detected(sp,1)=0;
                end
        end
                net_resource=sum(BO(na).NetResource(:,1));
                req_resource=sum(BO(na).Techrequired(:,1));
                BO(na).Quality=net_resource/req_resource;
    else
    end
end
```

D.3 Evaluation stage – rewarding routine

```
for na=1:Act_Crd.active_coord

if all(BO(na).SP)
    defect.         =zeros(length(BO(na).SP),4);
    net_resource.   =sum(BO(na).NetResource(:,1));
    req_resource.   =sum(BO(na).Techrequired(:,1));
    quality.        =net_resource/req_resource;
    total_profit.   =0;

    if quality >= BO(na).min_quality
        BO(na).awarding=1;
        cc_profit   =cc_profit;
        cc_price    =sum(Cost_Prt(:,BO(na).coord));
        cc_resource =mean(BO(na).OfferedResource);
        C_award_own =cc_profit*cc_price*cc_resource;
```

```
        ct_profit   =ct_profit;
        C_award_pt  =0;

        BO(na).p_CD=C_award_own;
        BO(na).p_OP=0;
        BO(na).p_CP=0;
        BO(na).c_OP=0;
        BO(na).c_CP=0;

        for sp=1:length(BO(na).SP)
            pt_price=sum(Cost_Prt(:,BO(na).SP(sp)));

            pt_price2=cost_coeff*(cost_coeff/pt_price);
            pt_resource=BO(na).OfferedResource(sp);
            sp_defect=BO(na).Defect(sp);
            sp_mntcost=BO(na).mnt_cost(sp);
            C_award_pt= C_award_pt+
ct_profit*pt_price2*pt_resource;

            if BO(na).SP(sp) <= 50

BO(na).p_OP=BO(na).p_OP+ct_profit*pt_price2*pt_resource;
            else

BO(na).p_CP=BO(na).p_CP+ct_profit*pt_price2*pt_resource;
            end
        end
             BO(na).profit=C_award_own+C_award_pt-
sum(BO(na).mnt_cost);
             Relation=1;
        for sp=1:length(BO(na).SP)
            Relation_Map(BO(na).coord,BO(na).SP(sp))=Relation*1;
            ct_profit=ct_profit;
            pt_profit=pt_profit;
            pt_price=sum(Cost_Prt(:,BO(na).SP(sp)));
            sp_defect=BO(na).Defect(sp);
            pt_resource=BO(na).OfferedResource(sp);
            pt_def_profit=pt_def_profit;
            sp_defect_profit=(pt_price)*(sp_defect);

CProfit_Map(BO(na).coord,BO(na).SP(sp))=
CProfit_Map(BO(na).coord, BO(na).SP(sp))
+ Relation*(pt_profit)*(pt_price)*(pt_resource);
Trust_Map(BO(na).coord,BO(na).SP(sp))=Trust_Map(BO(na).coord,
BO(na).SP(sp))+Relation*(ct_profit)*(pt_price)*(pt_resource);

            count_all_pt=count_all_pt +1;
```

```
            if BO(na).SP(sp) <= 50
                count_op=count_op+1;
                BO(na).c_OP=BO(na).c_OP+1;
            else
                count_cp=count_cp+1;
                BO(na).c_CP=BO(na).c_CP+1;
            end
        end
        pt_def_profit=pt_def_profit;

        for sp=1:length(BO(na).SP)

             if BO(na).SP(sp) <= 50

           pt_price=sum(Cost_Prt(:,BO(na).SP(sp)));
           sp_defect=BO(na).Defect(sp);
           LossPenalty=Relation*(pt_def_profit)*(pt_price)*(sp_d
           efect);

                 if BO(na).Detected(sp)==1
CProfit_Map(BO(na).coord,BO(na).SP(sp))
=CProfit_Map(BO(na).coord, BO(na).SP(sp))-LossPenalty;
Trust_Map(BO(na).coord,BO(na).SP(sp))=Trust_Map(BO(na).coord,
BO(na).SP(sp))
- LossPenalty;
Relation_Map(BO(na).coord,BO(na).SP(sp))=Relation_Map(BO(na).coo
rd, BO(na).SP(sp));
                    BO(na).profit=BO(na).profit;

                    if BO(na).SP(sp) <= 50
                        BO(na).p_OP=BO(na).p_OP;
                    else
                        BO(na).p_CP=BO(na).p_CP;
                    end
                 else

CProfit_Map(BO(na).coord,BO(na).SP(sp))
 =CProfit_Map(BO(na).coord, BO(na).SP(sp))+ LossPenalty;
                     BO(na).profit=BO(na).profit-LossPenalty;
                     BO(na).p_OP=BO(na).p_OP-LossPenalty;
                     if Part_Map(ActCoord_ID(na),3)==1
                        rc_penalty(t)=rc_penalty(t)+LossPenalty;
                     elseif Part_Map(ActCoord_ID(na),3)==2
                        sc_penalty(t)=sc_penalty(t)+LossPenalty;
                     end
                end
```

```
            end
        end
    else
        BO(na).awarding=0;
        BO(na).profit=0;

        if BO(na).SP(sp) <= 50
            BO(na).p_OP=0;
        else
            BO(na).p_CP=0;
        end
        Relation= 0;
    end
else
    BO(na).awarding=0;
    BO(na).profit =0;
    Relation= 0;
    BO(na).mean_mnt=0;
    BO(na).Quality=0;
    BO(na).p_CD=0;
    BO(na).p_OP=0;
    BO(na).p_CP=0;
    BO(na).c_OP=0;
    BO(na).c_CP=0;

end
```

D.4 Evaluation Stage - updating social capital of suppliers

```
for na=1:Act_Crd.active_coord

       if all(BO(na).SP)

        if  Part_Map(ActCoord_ID(na),3)==1

rc_profit(t)=rc_profit(t)+BO(na).profit*BO(na).awarding;

rc_consortium(t)=rc_consortium(t)+BO(na).awarding;
                rc_mtcost(t)=rc_mtcost(t)+sum(BO(na).mnt_cost);
                nop_rc(t)=nop_rc(t)+nnz(BO(na).Defect);

           rc_rtrust_avg(t)=rc_rtrust_avg(t)+mean(BO(na).r_trust
           );
           tmp_rc_rtrust_avg(t)=rc_rtrust_avg(t)+mean(BO(na).r_t
```

```
            rust);
            rc_strust_avg(t)=rc_strust_avg(t)+mean(BO(na).s_trust
            );
            defect_rc_avg(t)=defect_rc_avg(t)+mean(BO(na).DefectR
        );
            rc_adjdef_op(t)=rc_adjdef_op(t)+sum(BO(na).DefectR);
            rc_p_cd(t)=rc_p_cd(t)+BO(na).p_CD;
            rc_p_op(t)=rc_p_op(t)+BO(na).p_OP;
            rc_p_cp(t)=rc_p_cp(t)+BO(na).p_CP;
            rc_c_op(t)=rc_c_op(t)+BO(na).c_OP;
            rc_c_cp(t)=rc_c_cp(t)+BO(na).c_CP;

         elseif Part_Map(ActCoord_ID(na),3)==

            sc_profit(t)=sc_profit(t)+BO(na).profit*BO(na).awardi
            ng;
            sc_consortium(t)=sc_consortium(t)+BO(na).awarding;
            sc_mtcost(t)=sc_mtcost(t)+sum(BO(na).mnt_cost);
            nop_sc(t)=nop_sc(t)+nnz(BO(na).Defect);

sc_rtrust_avg(t)=sc_rtrust_avg(t)+mean(BO(na).r_trust);

sc_strust_avg(t)=sc_strust_avg(t)+mean(BO(na).s_trust);

defect_sc_avg(t)=defect_sc_avg(t)+mean(BO(na).DefectR);
            sc_adjdef_op(t)=sc_adjdef_op(t)+sum(BO(na).DefectR);
            sc_c_op(t)=sc_c_op(t)+BO(na).c_OP;
            sc_p_cp(t)=sc_p_cp(t)+BO(na).p_CP;
            sc_c_cp(t)=sc_c_cp(t)+BO(na).c_CP;
            sc_p_cd(t)=sc_p_cd(t)+BO(na).p_CD;

         end

Coordinator_ProfitMatrix(ActCoord_ID(na),t)=BO(na).profit;

         else
             nc_profit(t)=nc_profit(t);
             rc_profit(t)=rc_profit(t);
             sc_profit(t)=sc_profit(t);
         end

     end % END of for na=1:Act_Crd.active_coord

     np_cprofit(t)=sum(sum(CProfit_Map));
     op_cprofit(t)=sum(sum(CProfit_Map(:,1:50)));
     cp_cprofit(t)=sum(sum(CProfit_Map(:,51:100)));
     np_cprofit_avg(t)=mean(mean(CProfit_Map));
```

```
    op_cprofit_avg(t)=mean(mean(CProfit_Map(:,1:50)));
    cp_cprofit_avg(t)=mean(mean(CProfit_Map(:,51:100)));
    np_rtrust_avg(t)=mean(mean(Trust_Map));
    op_rtrust_avg(t)=mean(mean(Trust_Map(:,1:50)));
    cp_rtrust_avg(t)=mean(mean(Trust_Map(:,51:100)));
    np_rtrust_nnz_avg(t)=mean(mean(nnz(Trust_Map)));
    op_rtrust_nnz_avg(t)=mean(mean(nnz(Trust_Map(:,1:50))));
    cp_rtrust_nnz_avg(t)=mean(mean(nnz(Trust_Map(:,51:100))));
    ncp_nc(t)=nc_consortium(t)*length(BO(na).OfferedResource)-
nop_nc(t);
    ncp_rc(t)=rc_consortium(t)*length(BO(na).OfferedResource)-
nop_rc(t);
    ncp_sc(t)=sc_consortium(t)*length(BO(na).OfferedResource)-
nop_sc(t);

    temp_rtrust=nc_rtrust_avg(t);

    if nc_consortium(t)==0
       nc_rtrust_avg(t)=0;
    else
       nc_rtrust_avg(t)=nc_rtrust_avg(t)/nc_consortium(t);
    end

    if rc_consortium(t)==0
       rc_rtrust_avg(t)=0;
       tmp_rc_rtrust_avg(t)=0;

    else
       rc_rtrust_avg(t)=rc_rtrust_avg(t)/rc_consortium(t);
       tmp_rc_rtrust_avg(t)=tmp_rc_rtrust_avg(t);
    end

    if sc_consortium(t)==0
       sc_rtrust_avg(t)=0;
    else
       sc_rtrust_avg(t)=sc_rtrust_avg(t)/sc_consortium(t);
    end

    defect_nc_avg(t)=defect_nc_avg(t)/nc_consortium(t);
    defect_rc_avg(t)=defect_rc_avg(t)/rc_consortium(t);
    defect_sc_avg(t)=defect_sc_avg(t)/sc_consortium(t);
    nc_adjdef_op(t)=nc_adjdef_op(t)/nop_nc(t);

    if nop_rc(t)==0
        rc_adjdef_op(t)=defect_op;
    else
        rc_adjdef_op(t)=rc_adjdef_op(t)/nop_rc(t);
```

```
end

if nop_sc(t)==0
    sc_adjdef_op(t)=defect_op;
else
    sc_adjdef_op(t)=sc_adjdef_op(t)/nop_sc(t);
end

rc_amtcost(t)=rc_mtcost(t)/rc_consortium(t);
sc_amtcost(t)=sc_mtcost(t)/sc_consortium(t);

if t>2
    if isnan(rc_amtcost(t))
        rc_amtcost(t)=rc_amtcost(t-1);
    end

    if isnan(sc_amtcost(t))
        sc_amtcost(t)=sc_amtcost(t-1);
    end

    if isnan(rc_adjdef_op(t))
        rc_adjdef_op(t)=0;
    end

    if isnan(sc_adjdef_op(t))
        sc_adjdef_op(t)=0;
    end
end

%%%% Reputaton
Reputation_Map=Relation_Map;

if nc_consortium(t)==0
    nc_strust_avg(t)=0;
else
    nc_strust_avg(t)=nc_strust_avg(t)/nc_consortium(t);
end

if rc_consortium(t)==0
    rc_strust_avg(t)=0;
else
    rc_strust_avg(t)=rc_strust_avg(t)/rc_consortium(t);
end

if sc_consortium(t)==0
    sc_strust_avg(t)=0;
else
```

```
    sc_strust_avg(t)=sc_strust_avg(t)/sc_consortium(t);
end

np_strust(t)=mean(sum(Reputation_Map));
op_strust(t)=mean(sum(Reputation_Map(:,1:50)));
cp_strust(t)=mean(sum(Reputation_Map(:,51:100)));
```