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Investigating the underlying social psychology of the innovation adoption in container trucking industry

Abstract: Most extant literature in the transportation industry views innovation adoption as a rational choice process conducted on a cost-benefit calculation basis. This restricts our understanding of innovation decisions made by individuals embedded in a social-economic context. By investigating the underlying social psychology of the innovation adoption in the Chinese container trucking industry, this paper aims to answer the question as to 'why trucking operators postpone adopting the cargo-truck matching system during its early stage'. In order to achieve the research objective, a mixed methods research framework is proposed. First, we conduct four in-depth interviews using semi-structured questionnaires to investigate the contextualized behavior of individuals, based on which three hypotheses are developed. Second, based on the data collected from an online questionnaire survey covering 282 trucking operators in Ningbo, the proposed empirical hypotheses are tested using a discrete choice model. We find that risk tolerance positively moderates influence of the status quo on the innovation adoption decision, whilst the effect on it of service-orientation is negative.

Keywords: *Innovation adoption, Social psychology, Container trucking industry, Mixed methods, Platformization*

1. Introduction

Technological and managerial innovations are rapidly changing the traditional way of organization and production in the transportation industry. Chen et al. (2019) report on an innovative internet-based mode of industry organization in China that is significantly improving efficiency of the traditional freight forwarding industry. Although extant transportation literature has already identified innovation adoptions as being positively associated with an expectation of performance improvements, most of them are conducted on a cost-benefit calculation basis. For example, Subramanian et al. (2015) find that perceived reduction in cost triggered the adoption of integrated service and cloud computing among small and medium logistics providers; Similarly, Wang et al., (2018) support the idea that perceived usefulness has a positive effect on adoption intention, the effect on it of perceived risks is negative. Nguyen (2013) suggests that the principal components influencing e-business adoption decisions includes the large initial investment expense, financial constraints, and costs of operation etc; Oláh et al. (2018) study logistics service providers in Hungary, and reveal the fact that sector-specific information technology development is positively accompanied by a significant improvement in outcomes. It is noticed that the literature generally focuses on economic factors, but usually overlooks the underlying social psychology of innovation adoption, particularly in the early stages, which is of great importance to innovation diffusion in terms of accumulating enough seed users to trigger a bandwagon effect for the later stages. (Abrahamson and Rosenkopf, 1993). Orlikowski and Barley (2001) suggest that "Socio-technical systems theorists, for instance, who initially studied technologies as concrete objects and championed the idea that technical and social systems are reciprocally constitutive, … framed technology as a process that required inputs and produced outputs with degrees of variation". This indicates that innovation adoption should be considered as a back and forth process along with resistances and compromises, rather than assuming it to be a simple one-way process. As Orlikowski and Barley (2001) explain, most extant literature treats technology "as a material cause, of abstracting away from the specifics of a design, and of ignoring the role of a human agency". Abrahamson and Rosenkopf (1993) point out that, during the early stage of a two-stage model of innovation diffusion, when a high level of ambiguity renders unclear about "what returns", "the range of returns it may produce and the probability of these outcomes" and "whether returns expected from an innovation will be appropriate in future environments", the social process is even more important in achieving that critical number of seed users that will trigger the bandwagon effect for the second stage.

It is noticed that the analysis of underlying social psychology of innovation adoption in transportation research is still in its infancy. Therefore, this study focuses on the underlying social psychology of internet-based platformization in the Chinese container trucking industry, exploring the reason 'why trucking operators postpone adopting innovation during the early stage'. This study builds upon the previous literature by providing an alternative explanation complementary to the materialism-based view of innovation adoption in transportation literature. It will also enlighten practitioners, including both managers in the trucking industry and government agencies, so as to help them formulate better initiating strategies that will attract more usage, thus achieving the critical number of infusion seed users that will facilitate better diffusion in the later stages.

2. Literature review

Technological progress and management innovation are the prime factors driving efficiency improvement in the transportation industry. Therefore, innovation adoption has attracted much interest from academia. The question that has been widely addressed in the extant literature is about the factors leading to the adoption of innovation. Research has proved, in fact, that the adoption of new technology can be attributed to economic reasons (Oláh et al., 2018, Chen et al., 2019, Wolf and Seebauer, 2014, Petschnig *et al.,* 2014). For example, Liu et al. (2019) show that individuals with a higher income and who perceive higher benefits are more likely to pay for self-driving vehicles. Similarly, Wolf and Seebauer (2014) suggest that e-bike use is most driven by perceived usefulness, which in turn depends on an easy use, appropriate infrastructure. Chen et al. (2019) suggest that the adoption of autonomous vehicles should be promoted by subsidizing their purchase, with the objective of system optimization subject to a fixed budget. Zeng et al. (2018) comprehensively examine factors affecting the economic impact of logistics vehicles using electronic variable transmission hybrid power systems, estimating the cost and cost recovery cycle under different conditions. Their research affirms the economic advantages of the new practice. One recent study on electric van adoption shows that concerns related to range, queue, payload and electricity grid are reducing its acceptance among last mile operators in London and Paris (Morganti and Browne, 2018); management innovation adoption also reflects similar characteristics, as is the case too with new technology deployment. For example, the literature has also identified various factors that inhibit e-business adoption in supply chain management (Oliveira and Martins, 2010; Matopoulos et al., 2007). In a mixed methods case study, Gunasekaran and Ngai (2008) develop a conceptual framework for the adoption of e-procurement based on a questionnaire survey, identifying four constructs influencing the implementation of e-procurement, including perceived benefits of e-procurement, perceived barriers to e-procurement, critical success factors of e-procurement adoption, and perceived organizational performance with e-procurement. Nguyen (2013) finds that e-business adoption benefits service quality in terms of a higher level of competitiveness, service differentiation, and value adding, as well as improved customer service and supply chain integration. At the same time, though, Nguyen also highlights factors that inhibit the new practice, including the high initial investment expense, financial constraints, and costs of operation etc. Several studies also focus on the safety technology adoption in trucking industry. For example, Cantor, Corsi and Grimm (2006) find the larger firms, with a broad geographic scope of operations, are the leaders of the adoption. But few of them investigate into the mechanism by which innovation is adopted.

From the perspective of organizational sociology, the status quo of innovation adoption can be best described as materialism-oriented research, which, as Orlikowski and Barley (2001) suggested, refers to "conceptualized technology abstractly", "treated it deterministically (often as a material cause)" and "ignored the role of a human agency in shaping either the design or the use of the technology". In other words, the economic analysis in existing literature is based on a cost-benefit calculation. It detaches the innovation from its embedded context by ignoring the social factors involved, such as the interaction between technology and various adopters, user preferences, and political issues etc. In the remaining part of this section, we would like to briefly review two of the most popular innovation diffusion theories in sociology, these being the two-stage model (Rogers, 2003; Abrahamson and Rosenkopf, 1993) and the innovation resistance theory (Joachim et al., 2018; Talke and Heidenreich, 2013; Ram and Sheth, 1989). Both of these highlight the underlying social and psychological factors in innovation adoption. This literature helps to facilitate our theoretical development in section four.

Based on complete-information assumption, proponents of the two-stage model for innovation diffusion propose that little information about the consequence of innovation is disclosed during the early stage. Therefore, the potential adopters are cautious in innovation adoption, which results in a low speed of diffusion at the population level. As the number of adopters increases, more information about the innovation is released, which reduces the uncertainty and ambiguity of a new practice. Once a critical number of seed users is reached, the innovation becomes "infused with value beyond the technical requirements of the task at hand" as Selznick (1957) suggested. And the non-adopters tend to use the innovation to avoid illegitimacy and get support from their stakeholders (Meyer and Rowan, 1977), this being commonly referred to as institutional pressure or the bandwagon effect (Abrahamson and Rosenkopf, 1993).

The two-stage pattern highlights the importance of the critical number (also known as the threshold number) in innovation diffusion. It also has a limitation in reasoning why the early adopters decide to use the innovation. One possible explanation is that early adopters make their decision on a rational basis due to having a greater amount of private information, as well as due to their own characteristics (Rogers, 2003). However, innovation resistance theory challenges the rational decision view by pinpointing the existence of anti-change bias, which results from a generic predisposition of adopters to resist innovations prior to innovation evaluation (Talke and Heidenreich, 2013). This notion stems from Sheth (1981), who indicates that "the typical human tendency is to strive for consistency and status quo rather than to continuously search for, and embrace, new behaviors." Building upon previous literature on passive or active innovation resistance (Ram and Sheth, 1989; Laukkanen et al., 2008; Kleijnen et al., 2009), Talke and Heidenreich (2013) propose an integrated framework to theorize 'how to overcome anti-change bias' at the very beginning of the innovation diffusion. In considering whether Internet platform adoption in the Chinese container trucking industry is beginning to take off, Talke and Heidenreich's theory is quite suitable for investigating our research question.

The rest of this paper will be organized as follows: Background information will be provided in section three; in section four, we will introduce our mixed method research design and how we address our research questions combining qualitative and quantitative methods based on data collected from a questionnaire survey; section five presents theoretical hypotheses developed based on the innovation diffusion theories, and associated with four contextualized interviews; empirical analysis results will be displayed in section six, followed by the conclusion and implications in section seven.

3. Case Background: The Last Mile Revolution

Although a trucking service is considered to be the most appropriate method of accomplishing last mile delivery among various transport solutions, the Chinese container trucking industry features high fragmentation and a low level of regulation, which results in extreme inefficiency in its operation. For instance, due to information asymmetry, the no-load rate for Chinese road transport is up to 40% while that for

European and US market is about 20% and 10% respectively (He et al., 2017). This is a particularly common occurrence near container yards, which, in turn, results in loitering trucks and also places additional burden on the roads. At the macro level, it also contributes to the high cost of logistics in China nationwide that in 2016, for example, accounted for 14.6% of GDP[1]. Chinese central governance exhibited its ambition to restructure the trucking industry by issuing a policy to encourage Internet-based platformization in September 2016. The intended goal of the policy can be summarized as follows (also see figure 1), aiming to reshape the market structure to reduce the asymmetry of business information and improve market efficiency accordingly.

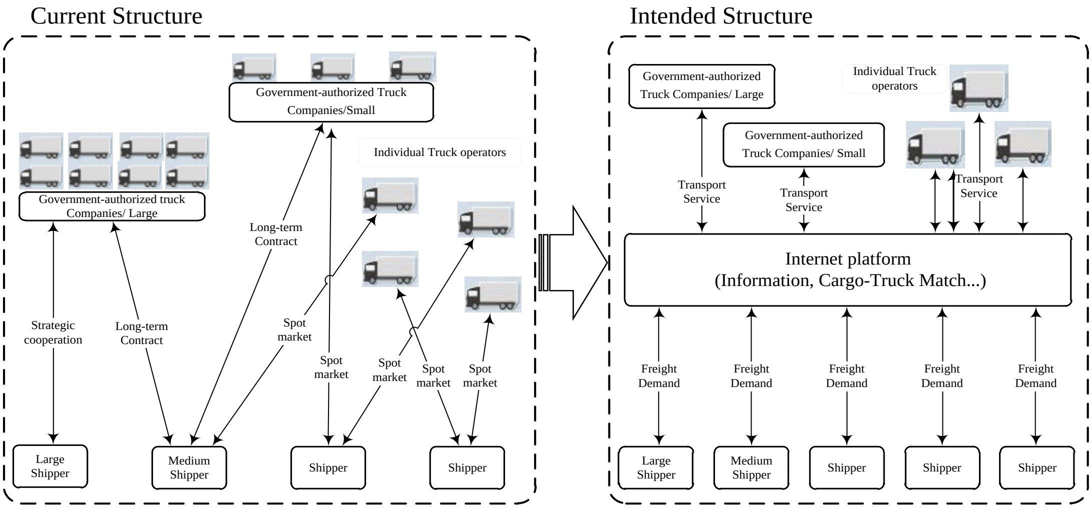

Figure 1. Current and intended structure of Chinese trucking industry (2016)

Currently, there are three main types of representative trucking operators in the market, including 1) large government-authorized truck companies, operating up to hundreds of vehicles; 2) small and medium size government-authorized companies operating a fleet of dozens of trucks; and 3) individual operators with less than 10 trucks (and even single-truck operators). In the container trucking niche market case, the large players are usually state-owned trucking companies affiliated to port groups. For example, Shanghai Logistics Company, which is affiliated to Shanghai International Port Group, operates more than 600 trucks, including 400 standard container trucks, and 100 dangerous cargo container trucks. These operators only serve certain companies, and rarely undertake freight tasks in the spot market,

[1] Source: National Development and Reform Commission's website, https://www.ndrc.gov.cn/xwdt/ztzl/jdstjjqycb/gzjz/201609/t20160901_1028613.html (access on Dec 5th 2019)

whereas small and medium size trucking companies are usually grassroots private enterprises, surviving amid fierce market competition. Although some of these companies have long-term contracts with several cargo-owners, mostly they receive commissions on the spot market to maximize the use of their trucks. Typical individual truck operators are those trucks operated independently under a registered company. The main purpose of this form of organization is to meet the market access requirements of the government, but due to lack of proper training and supervision the service quality of these companies is generally below average. Therefore, they can rarely get long-term contracts and operate on a spot market basis.

Inspired by the success of the sharing economy, such as with Uber and Airbnb, the development of information technology, such as internet, geographic information system etc., provides the current trucking market in China with a practicable solution to improve its efficiency which currently stuck with the asymmetry of market information. Therefore, the central government now encourages 'the last mile revolution' by advocating reconstruction of the market using the Internet platform, which is considered as excelling in information that can provide cargo-truck matching. Nowadays, however, this revolution is still in progress, and trucking operators are still feeling for the stones to cross the river, looking for the most suitable model to use in a Chinese context. In the consideration above, our study focuses on the underlying social psychology of the adoption of cargo-truck matching system, addressing research question as 'why trucking operators postpone adopting the cargo-truck matching system during its early stage?'

4. Research Design and Data Collection

Based on Johnson and Onwuegbuzie (2004) and Creswell (2009), we build a mixed-method research framework aiming to achieve a complete and comprehensive understanding of our research question. Pure qualitative research is seen as deficient for our research objective because of the potential for biased interpretations made by the researcher, and for the difficulty in generalizing findings to a large group, while quantitative research is also considered thin in understanding the context or setting in which people behave. On the other hand, by combining both, our research can endow the results with strengths that offset the weaknesses of each. Specifically, we develop our research hypotheses with qualitative data collected from four in-depth interviews held in the first stage during May 2017 to December 2017; and we then empirically test our hypotheses with quantitative data collected from self-administrated questionnaires (see appendix) in the second stage from January 2018 to June of 2018.

In the first stage, we conducted four semi-structured interviews with managers from trucking companies, and a trucking Internet platform respectively (also see table 1). Interview questions included, but were not limited to: 1) Introduce your company and business model; 2) Have you ever considered adopting an Internet platform-based business model? Why? (The trucking internet platform was excluded from this question); 3) What is the main advantage/disadvantage of an Internet platform-based business model in your opinion?

Table 1 List of Interviewees

Interviewee	Position	Affiliation
A	Operational Manager	Middle-sized trucking company X
B	Operational Manager	Middle-sized trucking company Y
C	CEO	Trucking Internet platform Z
D	Operational Manager	Trucking Internet platform Z

The main purpose of the interviews was to identify the social-psychological factors influencing adoption of the innovation, which has rarely been discussed in extant transportation literature. Based on the findings from the interviews, we then proposed three hypotheses as responses to our research questions.

The second stage validates the hypotheses we proposed in the first stage. To complete this, we further conducted a survey using online questionnaires. We collected 178 valid questionnaires out of 282 questionnaires distributed to individual trucking operators in Ningbo who are decision makers on using the platform. Compared to the large government-authorized trucking companies, they have higher tendency to use the platform in the early stage. Among all the questionnaires, 104 questionnaires were teased out of our empirical database due to their missing data and to data invalidity resulting from completing the questionnaires in an exceptionally short period (30 seconds), we finally have an effective return ratio of 63.1%. With the valid questionnaires, a logistic regression model was applied to validate the hypotheses we proposed. Figure 2 shows the mixed method research framework we designed to achieve our research objective.

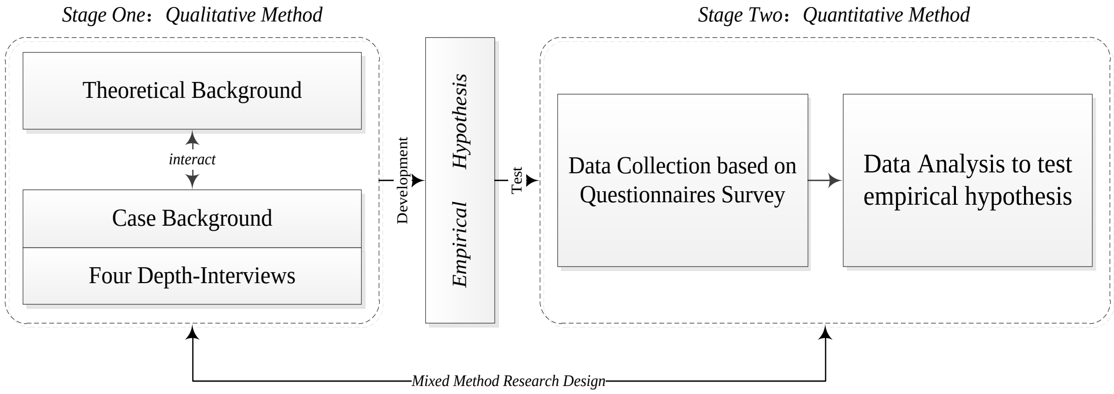

Figure 2. Mixed Method Research Design

5. Theoretical development and empirical hypotheses

5.1. *Theoretical development*

Individuals find it hard to recognize the existence of an alternative way of practice, especially for those who are satisfied with their status quo (Maguire and Lawrence, 2004). One possible explanation for this phenomenon is that socially embedded individuals are also shaped by their institutional context into what is an appropriate way of behavior, including social norms, values and usage pattern (Bagozzi and Lee, 1999; Ram and Sheth, 1989). Defaults have significant influence on individuals' decision (Park et al., 2000; Metcalfe & Dolan 2012). For example, Cantor, Corsi and Grimm (2008) find firms' priority for safety has significant influence on its decision on the adoption of safety technologies. These taken-for-granted approaches further blind them to recognizing alternatives. Talke and Heidenreich (2013) suggest "Such attachment often is irrational so that even alternatives with objectively superior qualities do not get considered". This phenomenon is also known as status quo bias (or anti-change bias) among innovation resistance theorists (Szmigin and Foxall, 1998; Gourville, 2006), and this further prevents innovation from stepping into the evaluation stage.

The evaluation stage can also be considered as a social-psychological process, one that does not unfold based purely on cost-benefit calculation and greatly influenced by what our attention is drawn to (Kahneman & Thaler, 2006). The innovation resistance theory is particularly applicable to the early stage of innovation diffusion when little information is disclosed due to limited scale of adoption at this point. According to the innovation decision model (Talke and Heidenreich, 2013;

Kleijnen et al., 2009; Ram and Sheth, 1989; Roger, 1976), potential adopters still have to overcome their functional and psychological barriers before making the innovation adoption decision. Functional barriers result from consumers perceiving that product attributes are dysfunctional or inadequate for personal needs and usage expectations (Bagozzi and Lee, 1999; Nabih et al., 1997, Talke and Heidenreich, 2013), including trialability barriers, complexity barriers, compatibility barriers, and co-dependence barriers, etc. Psychological barriers result from apparent conflict between innovation and consumers' social norms, values, or usage patterns, or if its usage is perceived as being too risky (Kleijnen et al., 2009; Ram and Sheth, 1989), including norm barrier, image barrier, usage barrier, economic risk barrier and social risk barrier etc. Based on the discussion above, we propose a two-stage innovation decision model for early adopters, as shown in Figure 3, this being the theoretical foundation for our contextualized empirical hypotheses in the rest of this section.

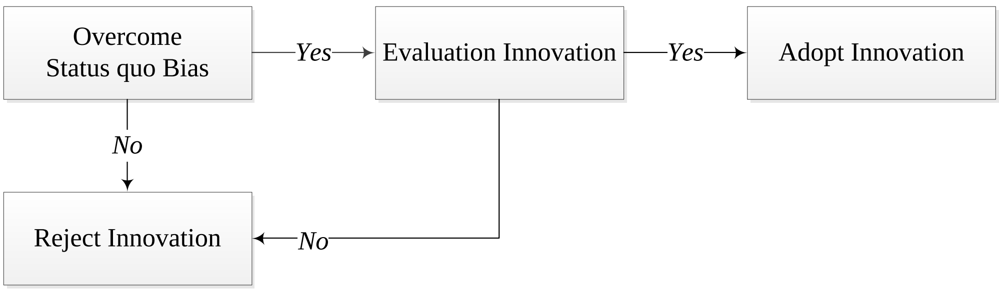

Figure 3. Two-stage innovation decision model for early adopters

5.2. ***Empirical hypotheses***

Trucking service is thought of as an under-paid industry with a low threshold for employment, particularly in those more developed provinces lying on the eastern coast of the country. It is noticed that most of the individual trucking operators in this industry are immigrants from the central and western provinces. Therefore, except for the formal organization shown in Figure 1, the trucking industry is also organized on an informal basis, as the migrant practitioners are used to frequently interacting based on their originating provinces, so that practitioners from the same province are more likely to interact with each other not only in business operation but also in their daily life. These informal connections shape practitioners' preferences, values and cognitive characteristics significantly. These informal connections shape practitioners' preferences, values and cognitive characteristics significantly, which plays as a reference point when they evaluate the innovation adoption's outcomes (Kahneman and Tversky, 1979). Especially, when the individual trucking operators mentally construe objects that are psychologically near to their reference point appears to be more detailed and contextualized features. When they mentally construe objects distal to their reference point, the construed objects are more like to be abstract and general (Trope, Liberman & Wakslak, 2007). This thus will influence their thoughts and behaviors. Reflecting on our case, in the city of Ningbo, where we conducted our case study, a large proportion of truck operators are originally from Anhui Province, which is located in the middle of China. If a local trucking company is owned and operated by people from Anhui, most of their employees will also come from the same province. Such trucking operators tend to share business information and cargo offers within their social group, which provides them with more business opportunities, creating a unique reference point compared with trucking operators coming from province other than Anhui. As suggested in the extant status quo literature (Szmigin and Foxall, 1998), such trucking operators are especially biased against the Internet platform-based business, because they are more satisfied with the status quo than are operators coming from other provinces which leads to an increase in the likelihood of them rejecting innovation. Therefore, we propose the first empirical hypothesis for our research question as follows:

***H1: Trucking operators (from Anhui) who are more satisfied with their status quo are more likely to reject Internet platform-based business innovation*.**

Once individuals overcome their status quo bias, they have to evaluate the innovation according to their own criteria, and this too is socially constructed. In our case, at the early stage of innovation diffusion, the trucking industry is also characterized by a higher level of ambiguity associated with usage risk and functional risk. This enhance individual's tendency to overweight potential losses than potential gains (Kahneman and Tversky,1979). To practitioners in the trucking industry, learning from the success of the sharing economy in other sectors, such as Uber and Airbnb, means promoting greater efficiency in industrial operations by integrating decentralized information into an Internet platform endowed with sophisticated technology. However, the other side of the story is that this innovation has to reshape the information flow embedded in an already established business pattern, which is considered will have potential negative effects on customers' experience. This is consistent with the notion of usage risk proposed in existing literature (Hoeffler, 2003; Ram and Sheth, 1989) referring to "the innovation's inconsistencies with past experiences that threaten to disrupt established usage patterns" as Talke and Heidenreich (2013) suggested. Similarly, some comments in our interview manuscripts echo the usage risk proposition as follows:

[1]…The government-authorized trucking companies are less likely to share their exclusive information with others, including the Internet platform, in being afraid of losing their competitive advantage as well as reducing customers' experience… (Comment by an individual trucking operator)

[2]…We identify ourselves as an information provider in order to avoid potential conflict of interests with trucking companies. This strategy also facilitates our cooperation with these companies in the future… (Comment by an Internet platform operator)

Furthermore, functional risks also can be identified. Functional risk refers to the function reliability and performance uncertainty (Ram and Sheth, 1989) during the early stage of innovation diffusion. For example, more than 20 technicians are employed in an anonymous Internet platform-based trucking company, and their main responsibilities are to improve the function and usage experience of the Internet platform based on customer feedback. At the time we conducted our interview in November 2017, this company had already released three major software upgrades that significantly enhanced their customers' experience. Although all the apparent risks may postpone trucking operators' decisions on innovation adoption, their influence may still vary among individuals. It is thus likely that individuals with a higher risk tolerance will adopt the innovation, whereas others will postpone their decision, waiting for additional information disclosure to reduce their caution. Therefore, we propose our second empirical hypothesis as follows:

H2: Trucking operator risk tolerance positively moderates the effect of their status quo bias on their innovation adoption decision.

Extant research also indicates that individuals tend to evaluate the investment required as well as the transitional cost resulting from adopting a new pattern compared to the old one (Nguyen, 2013; Woodside and Biemans 2005). For example, after a behavioral experiment, Noussai et al. (2004) highlight the fact that price is always the foremost consideration for consumers when they are choosing a new product. Dhebar (1996) suggests it is not the price, but concern about how well spent this investment really is on a long-term basis, that makes consumers postpone their decision about whether to adopt innovation or not. These findings are in line with the notion of economic risk barriers in innovation adoption, which refers to “perceiving that innovation's costs are too high and the investment would be a waste of financial resources” as Joachim, Spieth and Heidenreich, (2018) suggested. Reflecting on our case, we notice the fact that service-oriented trucking operators are the ones most welcomed by shippers in the current market and are offered a large number of orders. The following comment was also made by a manager in a small trucking company:

[3]…Well-trained and service-oriented trucking operators are the most valuable resources in the trucking market. Our customers are usually large manufacturers and international traders. They pay great attention to the quality and attitude of our service, and once we fail in meeting up to their requirements this will have serious consequences...

Therefore, trucking operators with service-orientation are less likely to shift to a new pattern, considering that they will have to pay a higher transitional cost than their counterparts with less service-orientation and insufficient orders in the current market. From the discussion above, we finally reach our third empirical hypothesis as follows:

H3: Trucking operator service-orientation negatively moderates the effect of their status quo bias on the innovation adoption decision.

In summary, we propose our empirical framework applied for trucking industry in China in Figure 4.

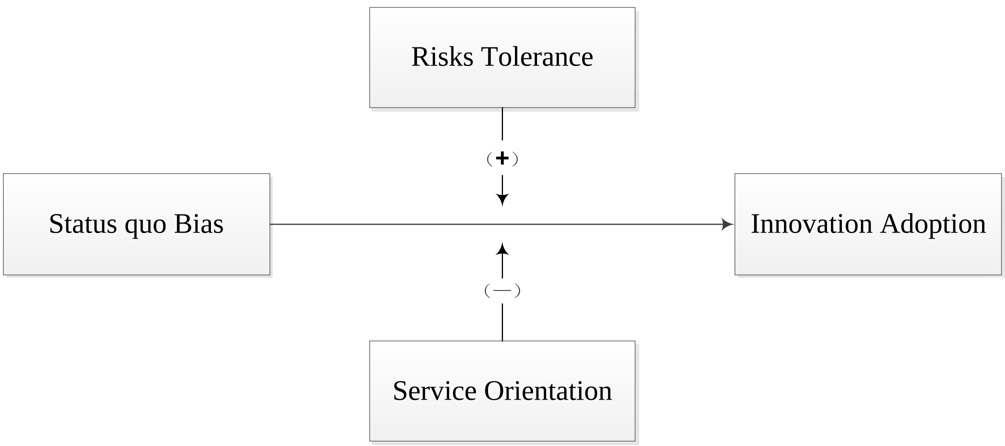

Figure 4. Empirical Framework

6. Data Analysis and Results

6.1 Model description

Using the survey data we collected, this section quantitatively tests our hypotheses in a logistic regression model. In the model, we denote P as the probability of *IA* (*Innovation Adoption*) =1 condition on our independent variables. Our logistic regression model is illustrated as follows:

$$\log(\frac{P}{1-P}) = \beta_0 + \beta_1 SQB + \beta_2 RT + \beta_3 SO + \beta_4 SQB \times RT + \beta_5 SQB \times SO + \beta_6 Gender$$
$$+ \beta_7 Age + \beta_8 EB + \beta_9 DE + \beta_{10} FS + \varepsilon \qquad (1)$$

Where *SQB* indicates the Status Quo Basis, *RT* means Risks Tolerance, *SO* is Service Orientation, *Gender* and *Age* denotes the gender and age of the trucking company operator respectively, *EB* is Educational Background, *DE* is Driving Experience and *FS* is Firm Size.

SQB is defined by whether the trucking company operator comes from Anhui, and is used to test hypothesis 1 (***H1***). We value the variable with 1 if the respondent comes from Anhui province, 0 otherwise; two moderate variables, including *RT* and *SO*, are measured in a "behavioral experiment" approach. The respondents are provided with the scenario test as follows:

Scenario I: When you are on your way to *C* to deliver a consignment, another customer offers you a shipment from *D* (as the "threaten to disrupt established usage patterns"). If you accept this shipment, you have to make a detour to receive the goods from *D*, which may result in the chance of a one-hour delay in the delivery to *C*. Will you accept the additional shipment?

A. I won't, because there is a chance of a one-hour delay in my delivery to C;

B. If the chance of a one-hour delay in the delivery to C is less than ***15%***, I will;

C. If the chance of a one-hour delay in the delivery to C is less than ***30%***, I will.

To avoid mutual interference among given options, in ***Scenario I*** we first ask the respondents to choose one option from **A** and **C**. In case they choose **A**, we further provide option **B** and ask them to choose one from **A** and **B**. We also adopt a similar questioning strategy for ***Scenario II***.

Risk tolerance (*RT*) is defined as a discrete variable, measured by the context-specific test in Scenario *I*. We value the construct with 3 if the respondent chooses A, 2 if the respondent chooses B, 1 if the respondent chooses C. This variable is used to test Hypothesis 2 (***H2***).

Scenario II: You are assigned to collect cargo at place Beilun at 10 o' clock tomorrow morning (Monday). If you are living in place Cixi, which is located 65 kilometers from Beilun, when do you plan to drive to Beilun to receive the cargo (meet up "the high requirement from customers") (Note: Regardless of traffic congestion, it usually takes about an hour to drive from Cixi to Beilun.)

A. Later than 09:00

B. 08:30 to 09:00

C. 08:00 to 08:30

D. 07:30 to 08:00

E. Earlier than 07:30

Service Orientation (*SO*) is also a discrete variable, measured by the context-specific test in Scenario II:

In Ningbo, it is quite common for container-trucking operators to pick-up containers in Beilun, where container yard is located, before they drive to the designated location for a delivery. Cixi is a county located 65 kilometers away from Beilun (also see figure 5). It usually takes about an hour to drive from Beilun to Cixi. There is always a traffic congestion on Monday morning due to few deliveries in the weekend. It thus normally takes more than one hour for the container-trucking operators to drive from Beilun to Cixi on Monday morning. As a result, if the container-trucking driver leave exactly one hour ahead of the delivery time, they are likely to be late. They know this fact very well, alternatively, some of them leave earlier to increase the chance of reaching their customers in time. With this in mind, we assume that the more additional time a container-trucking operator willing to sacrifice in order to ensure an on-time delivery, the more service-orientation the operator is. Based on this understanding, we design the Scenario II."

We value the construct with 1 if the respondent chooses A, 2 if the respondent chooses B, 3 if the respondent chooses C, 4 if the respondent chooses D and 5 if the respondent chooses E. This is used to test hypothesis 3 (***H3***).

We also control gender, age, education background (*EB*), driving experience (*DE*) and firm size (*FS*) in this model. Operating characteristics, including type of service, type of goods and etc., as suggested by Golob & Regan (2002) incorporated into our model due to the fact that our empirical setting limited to container trucking service, which provides customers with standard container collecting service from customers' warehouse/factory to container terminal. Therefore, we have excluded these counterfactuals resulted from operating characteristics among our respondents. The detailed description of variables in the model is presented in Table 2.

Figure 5 The geographic locations of Scenario II

Table 2. Description of Variables

Variable	Description	In questionnaire
Adoption status	1 if the respondent has used an Internet-based platform to receive orders, 0 otherwise;	Question 6
Status quo bias	1 if the respondent comes from Anhui Province, 0 otherwise;	Question 7
Risk tolerance	3 if the respondent chooses A, 2 if the respondent chooses B, 1 if the respondent chooses C;	Question 8/Scenario test
Service orientation	1 if the respondent chooses A, 2 if the respondent chooses B, 3 if the respondent chooses C, 4 if the respondent chooses D, and 5 if the respondent chooses E;	Question 9/Scenario test
Gender	1 if the respondent is female, 0 if the respondent is male;	Question 1
Age	0 if the respondent is under 28; 1 if the respondent is older than 28;	Question 2
Educational background	0 if the respondent's educational background is junior high school or lower; 1 if the respondent's educational background is senior high school or higher;	Question 3
Driving experience	0 if the respondent's driving experience is less than 12 years; 1 if the respondent's driving experience is more than 12 years;	Question 4
Firm size	1 if the firm size is less than 10 trucks; 2 if the firm size is between 11 and 20 trucks; 3 if the firm size is between 21 and 30 trucks; 4 if the firm size is more than 31 trucks.	Question 5

Methodology-wise, since we value the whether the technology is adopted with 0 and 1, while the independent variable, moderate variables and control variables are either dummy variable or count variables, the logistic regression fit our research well, enabling us to predict the values of a dichotomous dependent variable (Y) which takes only two values, 0 or 1, depending on a set of explanatory variables that can be either quantitative or categorical variables (Wooldridge, 2008).

6.2 Data Analysis and Results

The descriptive statistics for all variables and the correlations of the variables are reported in Table 3 and Table 4 respectively. We notice that most of the correlation values are below 0.5. Furthermore, we also conduct the Variance Inflation Factor (*VIF*) test. The mean VIF was 1.1, below the rule-of-thumb cutoff of 10 (Ryan, 1997). Therefore, we believe that multicollinearity does not significantly affect our results.

Table 3. Descriptive Statistics of Variables

	N	Mean	SD
Adoption status	178	0.53	0.5
Status quo bias	178	0.46	0.5
Risk tolerance	178	2.04	0.609
Service orientation	178	3.72	1.377
Gender	178	0.04	0.208
Age	178	0.75	0.433
Educational background	178	0.93	0.261
Driving experience	178	0.54	0.499
Firm size	178	2.69	1.133

Table 4. Correlations of Variables

	VIF	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Adoption status		1								
(2) Status quo bias	1.18	-0.831***	1							
(3) Risk tolerance	1.07	-0.190**	0.191***	1						
(4) Service orientation	1.09	0.075	-0.143*	-0.167**	1					
(5) Gender	1.10	0.094	-0.092	-0.061	0.103	1				
(6) Age	1.24	-0.327***	0.321***	0.150**	-0.248***	-0.127*	1			
(7) Education	1.03	0.170**	-0.087	-0.021	0.038	-0.043	-0.111	1		
(8) Driving experience	1.10	0.254***	-0.219***	-0.062	0.137*	-0.074	-0.262***	0.134*	1	
(9) Firm size	1.06	-0.021	0.038	0.037	-0.045	-0.227***	0.059	0.036	-0.035	1

Note, $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

The results of the logistic regression are presented in Table 5. Model 1 is the basic model, containing only control variables; Model 2 is the primary model to test hypothesis 1, containing independent variable and control variables; Model 3 is to test hypothesis 2, containing independent variable, moderator 1 (risk tolerance) and control variables; Model 4 is to test hypothesis 3, containing independent variable, moderator 2 (service orientation) and control variables. Model level VIF tests are conducted to make sure the multicollinearity does not significantly affect our results.

Model 1 contains control variables only, including gender, age, educational background, driving experience, and firm size. Except for firm size, all others are significant at 10% significance level. The gender, educational background and driving experience are positive, while age is negative. We found that gender has the largest impact on innovation adoption, followed by educational background. Older people are more likely to be resistant to innovation. This is consistent with reality.

In Model 2, the status quo bias is added. As shown, the status quo bias is negative (β =-4.780) and significant at 1% significance level, indicating that status quo bias negatively affects adoption status. Thus, hypothesis 1 (***H1***) is supported.

Table 5. Logistic Regression Results

Variable	Model 1	Model 2	Model 3	Model 4
Gender	1.209 (0.972)	0.928 (1.699)	0.894 (2.118)	1.311 (1.985)
Age	-1.458^{***} (0.442)	-0.791 (0.793)	-0.510 (0.863)	-1.405 (1.009)
Educational background	1.175 (0.720)	1.983^{**} (0.983)	2.629^{**} (1.144)	1.868^{*} (0.998)
Driving experience	0.807^{**} (0.337)	0.801 (0.576)	1.043^{*} (0.609)	0.692 (0.613)
Firm size	0.040 (0.149)	0.133 (0.252)	0.135 (0.263)	0.139 (0.258)
Status quo bias		-4.780^{***} (0.590)	-10.613^{***} (2.586)	-2.512^{*} (1.489)
Risk tolerance			-1.720^{**} (0.734)	
Service orientation				-0.004 (0.293)
Status quo bias × Risk tolerance			2.598^{**} (1.042)	
Status quo bias × Service orientation				-0.751^{*} (0.434)
N	178	178	178	178
Pseudo R-squared	12.49%	61.91%	65.03%	64.53%
VIF	1.08	1.11	4.56	3.16

Note, Robust standard errors in parentheses; $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

In Models 3 and 4, we examine the moderating effects of risk tolerance and service orientation respectively. In model 3, it is indicated that the interaction effect of status quo bias and risk tolerance on adoption status is statistically positive ($\beta = 2.598$) at 5% significance level, which supports our hypothesis 2 (H2). In model 4, we found that the interaction effect of status quo bias and service orientation on adoption status is statistically negative ($\beta = -0.751$) at 10% significance level, which confirms our hypothesis 3. It is worth noting that the value of pseudo R-squared from Model 1 to Model 4 increases from 12.49% to 64.53%, indicating a better model fit with the social-psychological factors.

Following De Veaux, Velleman and Bock, (2015), we conducted robustness check based on log odds ratios to justify the interaction effects. As shown in Equation (1), the log odds ratios can be estimated in the form of $\mathrm{Ln}\left(\frac{\hat{p}}{1-\hat{p}}\right)$, where $\hat{p}$ is the estimation of P defined in equation (1). The interaction effect between status quo bias and risk tolerance, Status quo bias and Service orientation are shown in Figure 6 and Figure 7, respectively. As shows in Figure 6, when risk tolerance values 1 (RT=1), the slope is -8.015, smaller than that of RT=3, which is -2.819. This means the possibility of innovation adoption of RT=1 reduces faster than that of RT=3 as predicted in H2. Similarly, Figure 7 shows that when service orientation values 1 (SO=1), the slope is -3.263, larger than that of SO=5, which is -6.267. This means the possibility of innovation adoption of SO=1 reduces slower than that of SO=5 as predicted in H3.

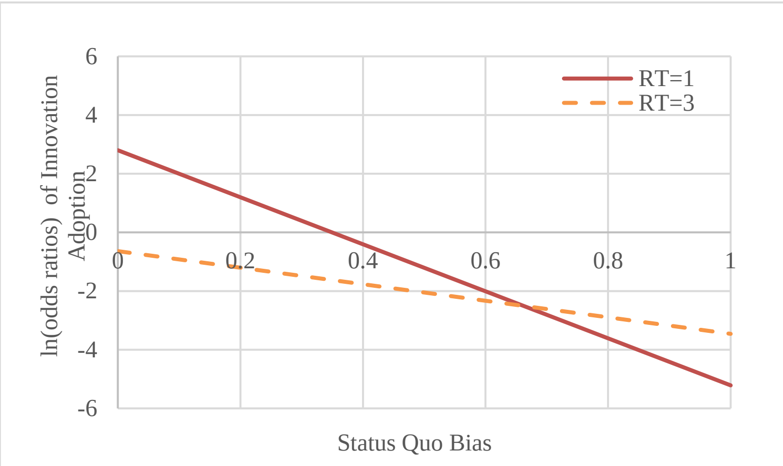

Figure 6 Interaction Effect Between Status quo bias and Risk tolerance on Adoption

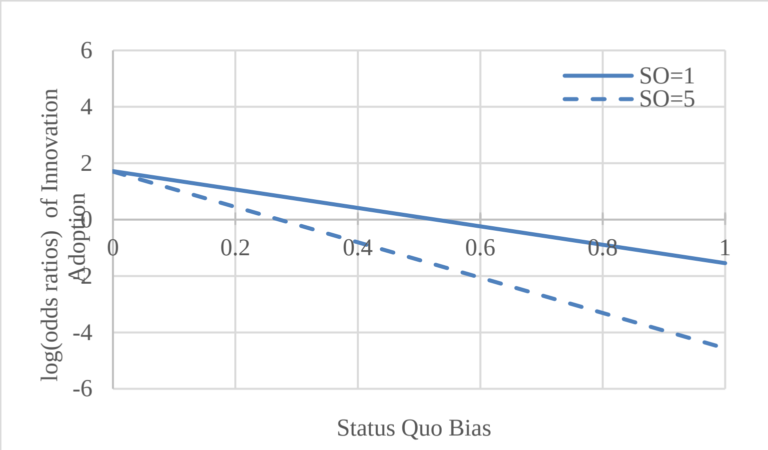

Figure 7. Interaction Effect Between Status quo bias and Service orientation on Adoption

7. Conclusions and Implications

Our research highlights the social-psychological factors underlying innovation adoption during the early stage in the transportation industry. In particular, rooted in innovation diffusion theory and innovation resistance theory, we develop a two-stage innovation decision model to explore its impact and test it empirically. We emphasize the fact that innovation diffusion may fail during the early stage simply because the potential adopters are not cognitively ready to accept new technologies and patterns, especially in the case of individuals who are more satisfied with their status quo. Furthermore, once overcoming the status quo bias, individuals proceed to the next stage of decision-making, where they have to evaluate innovation according to their own criteria. We propose that the evaluation stage also unfolds on a social-economic basis. A person's personality traits, such as sensation seeking, openness to experience, dogmatism, and locus of control, play an important role in the individual's inclination to adopt innovation. Using a case study regarding internet-based platformization in the Chinese container trucking industry, we empirically confirm our proposed hypotheses, namely, that risk tolerance positively moderates the influence of status quo bias on the innovation adoption decision, whereas the effect on it of service-orientation is negative.

The findings of this paper can help trucking company managers to understand the fact that technology excellence and cost advantage do not necessarily lead to success in introducing new products and patterns. Innovation adoption, usually associated with change in behavior, may conflict with existing social norms, values, and individual usage patterns, especially during the early stage when the economic benefits cannot be fully recognized due to limited information disclosure. Without sufficient incentives, individuals tend to strive for consistency and want to maintain the status quo, postponing their decision until the time is ripe. Therefore, attracting high risk tolerant and less service-oriented individuals to adopt a new business model (innovation) can be considered a practical approach to accumulating enough users to trigger the bandwagon effect. This roadmap is even more feasible if taking a proper training program, incentive plan and regulation into account, which can be regarded as a socialization process that follows an individual's innovation adoption.

As one of the preliminary studies focusing on the impact of social-psychological processes on innovation adoption in the transportation industry, the two-stage research framework we proposed in our research lays a good foundation and constructive reference for further researches in this field. In particular, our research framework provides a template for employing the same combination of qualitative method and quantitative method, leveraging their respective strengths to investigate the specifics of operator behavior. We believe that this approach is especially suitable for generating and testing theory in transportation studies that are rooted in the contextualized phenomenon. In the future, we think two promising directions in our framework are worthy of attention, including: 1) further refinement of the research model by introducing different variables in both stages. In particular, our results demonstrate that age has significant negative effect on the adoption of truck-cargo matching system while driving experience has significantly positive impact. This indicates that older driver tends to has less willingness to adopt the cargo-truck matching system. The driver with more experience is more likely to adopt the new technology. We also found that the gender and firm size is irrelevant to the new technology adoption in all models. Although these variables are not directly related to our research question, it still worth to investigate into the mechanism underlies this phenomenon for future research; and 2) focusing on more stages than just the early stage, by investigating the underlying mechanisms leading to innovation adoption decisions being made.

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Appendix: Questionnaire

Part A: Basic Situation

1. Gender: A．Male; B．Female.

2. Age: A. 23 and under; B. 24 to 28; C. 29 to 38; D. 39 and older.

3. Educational background:
A. Primary school or below;
B. Junior high school;
C. Senior high school;
D. Above senior high school.

4. Your truck driving experience:
A. Less than 6 years;
B. 7-12 years;
C. 13-18 years;
D. 19-24 years;
E. 25 years or above.

5．How many trucks do you have in your company?
A． 10 trucks or less;
B． 11 to 20 trucks;
C． 21 to 30 trucks;
D． 31 trucks or more

6. Have you ever received orders though an internet-based platform?
A. Yes;
B. No.

7. Your hometown: ______________(Province)

Part B. Scenario Choice:

8. ***Scenario I***: When you are on your way to C to deliver a consignment, another customer requests that you collect a shipment from D. If you accept this shipment, you have to make a detour to receive the goods from D, which may result in the chance of a one hour delay in the delivery to C. Will you accept the additional shipment？

a．I won't, because there is a chance of a one hour delay in my delivery to C;
b． If the chance of a one hour delay in the delivery to C is less than ***15%***, I will;
c．If the chance of a one-hour delay in the delivery to C is less than ***30%***, I will.

9. ***Scenario II***: You are assigned to collect cargo at place A at 10 o' clock tomorrow morning (Monday). If you are living in place B, which is located 65 kilometers from A, when do you plan to set off to drive to A to receive the cargo? (Note: Regardless of traffic congestion, it usually takes about an hour to drive from B to A.)

a. Later than 09:00
b. 08:30 to 09:00
c. 08:00 to 08:30
d. 07:30 to 08:00
e. Earlier than 07:30