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On-Demand Service Platforms Pro/Anti Adoption Cognition: Examining the Context-Specific Reasons

Abstract

The rise of digital platforms as new sociotechnical systems is profoundly transforming the market trajectory. Drawing on Behavioural Reasoning Theory, this study seeks to improve our understanding of consumers' rational decision-making and investigate how reasons influence motives and intentions toward using On-Demand Service Platforms (ODSPs). We empirically examined acceptance and resistance reasons in a single framework by analysing 523 respondents' data. The results demonstrate that the proposed model can explain the variance of consumers' rational decision-making in adopting or rejecting ODSPs. In addition, the findings underline the effect of reasons against on reasons for and the moderating role of inertia and perceived effectiveness of structural assurance in our research framework. Theoretically, current study contributes to the literature by realizing the influential context-specific reasons of prospective consumers for/against using digital platforms, highlighting the importance of consumers' loss aversion, and examining the moderating conditions. Practically, the results bring new insights for both managers and practitioners in line with the prosperity of digital platforms.

Keywords: On-demand service platform; Behavioural reasoning theory; Inertia; Perceived effectiveness of structural assurance; Context-specific reasons.

1. Introduction

The concept of the platform is not a new phenomenon, as we have experienced its traditional forms for years such as malls whereby customers are connected to merchants (Van Alstyne et al., 2016). However, over the last decade, digital technologies have profoundly transformed the way platforms generate value for all participants, especially by increasing data assets and decreasing the need for physical infrastructures. The emergence of on-demand service platforms (ODSPs) as economic networked-based systems, serving the role of intermediaries to fill short-term needs of consumers/clients by individual service providers, empowers a new form of digital economy, so-called on-demand economy. The underlying business model of ODSP firms is to serve people with what they want and where they want and to create value by enabling, directing, and constraining social and economic interactions (Perren and Kozinets, 2018). ODSP firms gain income by charging fees for linking workers offering on-demand services with consumers and businesses willing to pay for them (Kuhn and Maleki, 2017). As a service-providing intermediary, ODSPs assemble technology and networking in sophisticated ways to increase convenience, simplify decisions, and provide services that are superior to the ones actors could achieve on their own. These capacities have promoted new business opportunities and stimulate the emergence of new type of on-demand services.

The rise of digital platforms, which provide on-demand services, enables a wide range of applications in various areas: transportation (e.g., Uber, Lyft), delivery (e.g., Deliveroo, Postmates), household and personal (Taskrabbit, Handy), and specialized services (Medicast, Glamsquad). ODSPs are generally consisted of several parties contributing to the dynamic exchange agreement for providing on-demand services, typically trilateral, or sometimes quadrilateral relations. Today, consumers can use ODSP apps to order instant delivery of foods and groceries, to hire drivers for their commuting, to employ highly skilled workers for professional or creative jobs, to find local handymen to move and set up new furniture, and to arrange for someone to clean the homes or offices (Kuhn and Maleki, 2017). In the context of our research, ODSPs are those new technological systems that act as an intermediary, offer several potential benefits such as creating the on-demand service marketplace, facilitating the service search, checking service providers' background, processing and handling the payments after satisfactorily job completion, providing consumer care, and supplying liability insurance.

However, the ever more widespread of ODSP and their complex multi-sided nature raise new challenges, particularly in respect of identifying or developing behavioural models that represent underlying determinants influence consumers' adoption or resistance toward these platforms. The behavioural and decision-making science literature identifies consumer adoption/resistance to novel technological systems as a form of positive/negative intention or reaction to new products and services

that shift behaviours or make changes in the current situations (Chouk and Mani, 2019). Given the high failure rate of new products and services and the increasing power of consumers, identifying and developing behavioural models that represent fundamental adoption/rejection determinants of new technological systems are crucial. Nowadays, consumers can easily express their acceptance or resistance by adopting/rejecting the new systems, attending/boycotting the events, spreading positive/negative word of mouth, or supporting/disapproving companies. Furthermore, scholars argue the reasons for participating in digital platforms are not crystal-clear as previously thought, because of various users' motives and special characteristics of each contexts (Bucher et al, 2016).

Theoretically, the extant literature regarding technology adoption is limited in several areas. First, a large part of the existing research associated with new technological systems focus on the adoption process and its success factors (Cenfetelli and Schwarz, 2011). Dominant adoption theories such as the technology acceptance model (TAM) (Davis, 1989), or unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003) have been widely used to identify core constructs for the adoption of new IS. However, it is important and necessary to explore and examine the adoption inhibitors, which are not necessarily the opposite of adoption enablers (Cenfetelli and Schwarz, 2011; Park and Ryoo, 2013). As using new systems requires behavioural transformations and accepting changes in price, performance, routines, habits, or even traditions and norms (Garcia et al., 2007; Meuter et al., 2005), the rate of failure is high. Therefore, it has been argued that it is crucial to consider both enablers and inhibitors at the same time to understand the importance of mutually favourable and unfavourable reasons for technology acceptance (Cenfetelli and Schwarz, 2011). Second, the majority of adoption research has examined information technology usage in the organizational context (DeLone and McLean, 1992, Venkatesh et al., 2003), and the consumers' view receives less attention (Vekatesh et al., 2012; Laukkanen, 2016), resulting in comparatively fragmented understanding of why and how consumers adopt (or resist) novel technologies and services. Third, on-demand service model transforms the ways businesses serve consumers in almost every industry (van der Burg et al., 2019; Taylor, 2018), and digital platforms change the way this type of services are delivered or conceived. ODSPs have special features and affordances that facilitate searching services and transactions between different parties, and also apply different governance mechanisms to instil trust and gain legitimacy (Perren and Kozinets, 2018). Such capacities offer new opportunities for providing on-demand services, and ODPSs by leveraging technology alongside institutional arrangements can form an environment that intermediate and simplify exchanges between consumers and independent service providers. This transformation opens up the way for radically new context for providing and experiencing on-demand services. However, few studies have examined on-demand services, especially in digital platforms context, leading to call for developing new empirical insights, new concepts, and theory development in this field (De Reuver et al., 2018; Constantinides et al., 2018). Fourth, most of the previous studies in adopting new systems have conceptualized determinant factors as broadly construed behavioural beliefs, such as 'relative advantage which can convey almost anything from economic profitability to social benefits or time saved' (Cluady et al., 2015, p. 532). For instance, Hong et al. (2014) stress the inability of many behavioural studies to deliver clear and applicable results due to failure of differentiating the capabilities and purposes of the technology in different contexts. Some other scholars highlight the essential role of service type and context characteristic in consumers' adoption decisions (Nysveen et al., 2005; Laukkanen, 2016), and suggest that identifying contextual factors may develop richer theories that can provide more realistic knowledge and actionable advice (Weber, 2003).

Against these backdrops, the main goal of the present study is to gain a clear insight into the reasoning and decision-making process of consumers' adoption or resistance toward ODSPs. To address this goal, our main question is whether and how context-based reasons play significant role in ODSP consumer adoption intention. In particular, this research contributes to the literature by drawing upon and extending behavioural reasoning theory (BRT), to advance our understanding of the dichotomous nature of determinant factors for adopting or resisting an ODSP. In line with our research objective, we: i) respond to the call for paying deeper attention to the context in providing a theory that is more rigorous and incorporating relevant constructs of emerging technologies (Hong et al., 2014) and infer from both research streams and stakeholders' viewpoints to identify the context-specific *reasons for* and the *reasons against* the adoption of ODSPs, ii) attempt to provide a comprehensive insight about the

customers' decision logic by exploring and examining context-specific reasons serving as influential factors for attitudes and behavioural intentions (Westaby, 2005), iii) explain people's intention variance in using ODSPs beyond the traditional frameworks such as the theory of planned behaviour (TPB) (Claudy et al., 2015; Westaby et al., 2010; Westaby, 2005), by integrating situational opportunities and constraints that affect the consumers' behaviour (Johns, 2006).

Moreover, we extend BRT by responding to the Westaby's (2005) call for deeper scientific comprehension of behaviour through including external factors that are theoretically relevant. Therefore, we incorporate 'Perceived effectiveness of structural assurance (PESA)' and 'inertia' as moderators into BRT. Investigating the possible synergistic impacts of PESA and inertia with other variables would generate insights into the conditions under which reasons for or reasons against are especially effective in driving attitude and intention. We also examine the effect of 'reason against' on 'reason for' in the context of ODSPs. This consideration is an answer to the suggestion of Westaby (2005) to further exploring new linkages between constructs during the decision-making process, as well as designing empirical studies to test the effect of inhibitors on enablers in technology adoption literature (Cenfetelli and Schwarz, 2011). Practically, the results of this study would provide more precise and actionable advice to managers and enable them to effectively distinguish situational factors such as context-specific *reasons for* and *reasons against* adoption, and deliver greater details of how innovative technological systems such as ODSPs can be adopted and used (Hong et al., 2014).

The paper proceeds as follows: we first review the theoretical background and propose the conceptual model and the hypotheses. We then present our integrated approach to identify context-specific reasons and evaluate the hypothesis. We continue the paper with the results and discussion. Finally, we wrap up with theoretical and practical implications, conclusion, and suggestions for future studies.

2. Theoretical Background

On-demand services through digital platforms have attracted significant consumer attention and spending (Colby and Bell, 2016). Given its impressive rise, this new trend has been heralded as an on-demand economy which is comprised of a rapidly growing set of platforms that allow consumers access to services 'immediately when experiencing a need, anywhere and anytime' (van der Burg et al., 2019, p. 740). This growth is driven by both technological developments and changing consumer requirements. On-demand transactions are normally facilitated by technology platforms that enable accessing and offering services to be scaled by efficiently connecting or matching service providers and consumers (Perren and Kozinets, 2018). Digital platforms employ sophisticated algorithms for hiring individual service providers to perform tasks remotely or in-person for customers and monitoring the fairness and security of the system, ensuring that the transaction proceeds as desired. It has been argued that on-demand platforms are changing consumer habits, regulations, competition, and supply chains (Colby and Bell, 2016; Steinmetz, 2016).

The on-demand economy largely depends on service model innovation and transforms the ways businesses serve their customers and generate value. ODSP, as a novel technological system, has various consequences for consumers and changes their expectations and service experience in terms of convenience, speed, and simplicity. Consumers benefit from the new way services delivered by digital platforms and their governance mechanisms- for instance, searching service marketplace, selecting service providers based on reputation and feedback systems, and making secure payments. Despite the several opportunities offered by ODSPs, major challenges remain to be addressed regarding consumers' potential behaviour toward this novel multilateral systems. Consequently, it is important to examine the logic of decision-making process and antecedents underlying customer reactions to these technological systems.

2.1. Pro/Anti Adoption of a New System

Widely applied behavioural models such as TAM (Davis, 1989), TPB (Ajzen, 1991), UTAUT (Venkatesh et al., 2003), extended UTAUT (Venkatesh et al., 2012), and IS success model (DeLone and McLean, 1992) only cover adoption enablers, such as the usefulness, quality, and reliability of a

system. However, since the cognitive process to reject a new system cannot be described by the same reasons that justify acceptance (Gatignon and Robertson, 1989), several scholars urge examining factors that lead consumers to resist a system or technology (e.g. Antioco and Kleijnen, 2010; Claudy et al., 2015). Indeed, adoption and resistance toward a new system may coexist (Ram, 1987), and individuals may hold perceptions of enablers and inhibitors of accepting and resisting a new system simultaneously (Cenfetelli and Schwarz, 2011). Therefore, in exploring consumers' interactions with new technological systems, jointly answering questions of 'what are the reasons encouraging an individual to use a platform' and 'what are the reasons discouraging an individual to use a platform' advance our knowledge on ODSPs' adoption. In this study, we use BRT to answer the research questions as it enable us to effectively differentiate between factors influencing adoption/resistance, and assess the impact of these theoretically different antecedents in a single behavioural decision framework (Westaby, 2005).

2.2. Reasons for and Reasons against Adopting a New System

Reason theory posits that reasons motivate behaviour as they enable individuals to justify and defend their decisions (Westaby and Fishbein, 1996). People have reasons for their behaviour and use them to justify their actions (i.e., individuals do what they do because they have the desire to reach a goal and use the justifiable reasons for pursuing it). According to the theory of explanation-based decision-making, individuals apply reasons for evaluating the decision alternatives (Pennington and Hastie, 1993) and the more reasons justify and explain choosing an option, the more likely that alternative will be selected with confidence (Westaby, 2005). Further, according to functional approaches, any endeavour to alter the status quo would succeed only if the underlying reasons or functions of that behaviour change (Snyder, 1992). Generic behavioural intention models like TAM, TPB, and UTAUT have greatly advanced our fundamental knowledge of behaviour. However, these models have not addressed if or how context-specific reasons provide unique insight into justifying and defending mechanisms. Previous research demonstrates that context-specific reasons have predictive power and validity in people's judgment and decision-making process (Westaby, 2005; Chatzidakis and Lee, 2013). Context-specific reasons are instrumental in consumers' behaviour because they provide causal explanations for sensing their environment, behaviour and the behaviours of other consumers. In BRT, reasons play a focal role and have been defined as 'the specific subjective factors people use to explain their anticipated behaviour' (Westaby, 2005, p. 100). BRT framework considers two overarching reasons: 'reasons for' (RF) and 'reasons against' (RA) that motivate behaviour. This dichotomous differentiation of motivational forces is in line with common dual-factor studies, that all stemming from Herzberg's motivation theory (e.g. Lee et al., 2009; Cenfetelli and Schwarz, 2011; Park and Ryoo, 2013). However, most of these two-factor studies have not considered explanation-based processes and overlooked context-specific enablers and inhibitors of behaviours.

Reasons are conceptually different from beliefs. While beliefs represent a person's subjective probability judgements about potential future outcomes of a specific behaviour, the reasons refer to the subjective probability that a specific factor is part of the person's behavioural explanation set for that behaviour (Westaby, 2005). For instance, a consumer can strongly believe that using a digital platform would result in excellent benefits, self-worth, and good image in the eyes of others (i.e., multiple strong beliefs) but she may not use the system because of strong reasons against (e.g. service providers are not available or respond with high delay). Thus, the reason is the central cause of the decision and explains the personal justification for the behaviour.

Studies in the stream of technology adoption have mainly concentrated on how perceptions of new technological systems influence people's likelihood to adopt. The most frequently mentioned constructs that determine technology adoption are: perceived usefulness (Bhattacherjee, 2001; Lin and Bhattacherjee, 2008), perceived ease of use (Venkatesh and Davis, 1996), perceived pleasure (Bruner and Kumar, 2005), compatibility (Wu and Wang, 2005), perceived user base (Rogers, 2003) and personalization (Komiak and Benbasat, 2006).

On the other stream of technology adoption, scholars suggest anti-adoption factors that are not simply the opposite or lack of adoption factors (Claudy, 2015; Cenfetelli and Schwarz, 2011). To understand the backgrounds of customer resistance, various behavioural frameworks have been introduced (Ram

and Seth, 1989; Bagozzi and Lee, 1999). The investigated inhibitors in literature principally have been divided into functional and psychological barriers of using emerging technologies (Ram and Sheth, 1989). The highlighted anti-adoption factors are usage barriers (Laukkanen et al., 2007), value barriers (Lian and Yen, 2013), risk barriers (Herzenstein et al., 2007), image barriers (Antioco and Kleijnen, 2010), tradition barriers (Ram and Sheth, 1989), and technology anxiety barriers (Evanschitzky et al., 2015).

2.3. Framework and Hypotheses

As noted earlier, BRT provides the overarching hypothetical structure of this study. The main theoretical proposition in BRT is that reasons serve as the underlying determinant of beliefs and behavioural intentions. Figure 1 shows the theorized relations for our study according to the BRT. According to BRT conceptualizing of reasons as dichotomized dimensions of RF and RA adoption, we consider them as the fundamental antecedents of attitudes (H1a; H1b) and intentions (H2a; H2b), which predicts them through justification and defence mechanisms. Hence, BRT allows for different cognitive paths or processes in behavioural decision-making, which is contextual and provides a deeper understanding of factors that lead to both the adoption and resistance of platform technologies. In this study, we also consider the negative relationship between RA and RF (H3a) to understand the potential influence of loss aversion on gain perception in consumers' decision-making toward using ODSPs. Also, the moderating effects of RA on the relationship between RF and attitude (H3b) as well as intention (H3c) are considered. Consistent with other behavioural models like TPB, attitude is perceived as a main predictor of intention (H4). Finally, we incorporate two influential moderators PESA (H5a-H5d) and inertia (H6a-H6d) as external factors to extend our understanding of BRT in this context.

Reasons

BRT postulates that reasons are fundamental determinants of attitudes towards a behaviour. Because when people have strong reasons for a behaviour that justify it, they form favourable evaluations towards doing that behaviour (Westby, 2005). In the context of this study, attitude generally reflects users' opinion about the concept of ODSP, while reasons both for and against adoption involve specific factors that may influence their adoption attitude. According to BRT, justification mechanisms based on assessing reasons play a central role in judgement formation and decision-making process (Westby, 2005). Therefore, we suggest reasons impact attitudes towards adopting ODSP. Customers with justifiable reasons for/against accepting the digital platform would correspondingly have positive/negative attitudes towards it. This is in line with other theories such as explanation based decision-making (Pennington and Hastie, 1993) and spreading-activation theory (Anderson and Pirolli, 1984), which assert that strong reasons for a behaviour would lead to higher levels of cognition and explanation associated with the same considered behaviour. Similarly, BRT suggests that reasons serve as important antecedents of attitude, which is consistent with the fact that reasoning mechanisms play a powerful role in judgment formation (Hsee, 1996). To elaborate, when a person has strong reasons for undertaking a behaviour, the likelihood of activating abstract behaviourally related beliefs like positive attitude would increase. Following the BRT logical system, we hypothesize that:

Hypothesis 1a. Reasons for adopting on-demand service platforms will be positively related to attitude towards adoption.

Hypothesis 1b. Reasons against adopting on-demand service platforms will be negatively related to attitude towards adoption.

BRT also posits that based on the logically explained behaviour, context-specific reasons might directly contribute to the explanation of behavioural intentions beyond that explained by attitudes (Westaby, 2005). The direct impact of reasons on adoption intention is easily justifiable by the logic of decision-making or understanding the cognitive map of users' behaviour. Typically, users make their decision more easily, when there are strong reasons that defend or rationalize their intentions or decisions, even if their attitudes be different. For instance, a consumer may have a positive attitude toward adopting a new system but decide against using it because of price reason. Former technology adoption theories such as TAM and UTAUT also indicate the importance of technology characteristics as antecedents of users' adoption intention. We thus hypothesize that:

Hypothesis 2a. Reasons for adopting on-demand service platforms will be positively related to adoption intentions.
Hypothesis 2b. Reasons against adopting on-demand service platforms will be negatively related to adoption intentions.

We also theorize that RA affect RF. According to Cenfetelli and Schwarz (2011), RA may be especially important because of their potential impact on positive reasons. The Kahneman and Tversky's (1992) cumulative prospect theory asserts that individual decision-makers perceive values of gains and losses and behave based on two features of 'diminishing sensitivity' and 'loss aversion', that can be used to explain individuals' decision about uncertainties and risks (Olya and Han, 2019). Diminishing sensitivity indicates that people are risk-averse and more cautious about losses and loss aversion implies that losses overshadow gains in making decisions under uncertainty and risk conditions (Kairies-Schwarz et al. 2017). Extending cumulative prospect theory to the technology adoption, RF are equivalent to gains or potential gains and RA are comparable with losses or possible losses (Cenfetelli and Schwarz, 2011). Further, cue-diagnosticity theory (Skowronski and Carlston, 1987) and social judgment theory (Yzerbyt and Leyens, 1991) support the argument that negative beliefs are more diagnostics and explanatory than the positive viewpoints (Cenfetelli and Schwarz, 2011).

Grounded on these theories, we extend the theory of behavioural reasoning and suggest that consumers not only evaluate RF and RA separately but also assess RA disproportionately higher than RF and may consider them as diagnostic basis for evaluating new systems. Thereby, RA are more apparent and salient than RF (Cenfetelli and Schwarz, 2011) and can negatively influence the evaluations of positive reasons in adopting the ODSPs. Accordingly, we hypothesize the following:

Hypothesis 3a. Reasons against will negatively influence reasons for adoption.

Hypothesis 3b. Reasons against negatively moderate the relationship between consumers' reasons for and their attitude toward adoption.

Hypothesis 3c. Reasons against negatively moderate the relationship between consumers' reasons for and their adoption intention.

Attitudes
Studies on human logical behavioural intention, which is strongly associated with the intention belief, demonstrate that attitude play a critical role in predicting and regulating behavioural intention (e.g., Austin and Vancouver, 1996; Fishbach and Ferguson, 2007; Elliot and Fryer, 2008). In our study, attitude as a global motive reflects an individual's general positive or negative evaluation toward using ODSPs (Westaby, 2005). BRT considers attitude as an influential antecedent factor that constantly impacts intention across diverse behavioural domains (Ajzen, 2001). In accordance with the literature, we thus hypothesize that:

Hypothesis 4. Attitudes toward adopting on-demand service platforms will be positively related to their adoption intention.

Perceived effectiveness of structural assurance

ODSPs as digital labour marketplaces are similar to traditional e-commerce platforms, like Amazon or eBay, yet they function as intermediaries for on-demand service exchanges rather than product exchanges. Digital platforms and subsequently trusting in them do not operate in a vacuum (Gefen and Pavlou, 2006). In essence, they are subset of the larger market environment and societal structure (Doney et al., 1998) such that are affected by the way these supersets are regulated (Fukuyama, 1995). Thereby, prior studies argue that trusting beliefs about digital platforms form in a hierarchical structure (Park and Tussyadiah, 2019), that is in transactional, local (platform), and institutional levels. Exchanges in ODSPs involve more social relations than in other platforms like Amazon. Even they

often have multistage relations that involve not only online, but also offline interactions (Park and Tussyadiah, 2019). ODSPs customers predominantly transact with new and unknown service providers and may perceive various economic, safety, and security risks (Ert et al., 2016). Trusting belief in the transaction level of ODSPs implies that the service provider is competent, committed, and have good motives, thereby a customer can rely on her. In addition, customers have some interactions with the platform firms, they may thus have security and privacy concerns regarding using platform applications to disclose their personal information and their needs. Trusting in platform firms means that they do not misuse customer information and have established governance mechanism such as escrow services, guarantees, and feedback systems to mitigate risks and prevent opportunistic behaviours.

Beyond these two levels, is institution-based trust that is 'neither transaction-specific nor platform-specific' (Fang et al., 2014, p.410). Institution-based trust comes from sociology and is a belief that society and its market environment have solid structural and institutional settings to support frictionless social interactions (McKnight and Chervany, 2001). Perceived effectiveness of structural assurance (PESA), as one of the dimensions of institution-based trust, refers to users' general belief that structures like regulations, legal bonds, policies, or other safeguards are in place to promote social exchanges in markets. In this study, we suggest that PESA can be considered as a means to resolve consumers' uncertainties and may have synergistic relationships with *reasons for* affecting consumers' intentions to adopt ODSP. Similarly, previous studies also suggest that trust at one level alone may not be universally sufficient for triggering customer adoption intentions (e.g. Gefen and Pavlou 2006; Park and Tussyadiah, 2019). Indeed, PESA improves consumers' initial trust in the platform because consumers require to be protected from financial, informational, or other risks and uncertainties (McKnight et al., 2002). Consumers with higher evaluations of PESA will be more willing to consider *reasons for* rather than *reasons against* and develop a more positive attitude and stronger intention to adopt the platform. By contrast, when evaluations of PESA are low, the *reasons for* will be less salient and *reasons against* would be more significant in forming consumers' attitude and intention to adopt digital platform services. Therefore, the following hypotheses are proposed:

Hypothesis 5a. PESA positively moderates the relationship between consumers' reasons for and their attitude toward adoption, such that the positive effect of reasons for on attitude are strengthen when PESA is higher.

Hypothesis 5b. PESA positively moderates the positive relationship between consumers' reasons for and their adoption intention, such that the positive effect of reasons for on adoption intention are strengthen when PESA is higher.

Hypothesis 5c. PESA negatively moderates the relationship between consumers' reasons against and their attitude toward adoption, such that the negative effects of these reasons on attitude are weakened when PESA is higher.

Hypothesis 5d. PESA negatively moderates the relationship between consumers' reasons against and their adoption intention, such that the negative effects of these reasons on adoption intention are weakened when PESA is higher.

Inertia

Polites and Karahanna (2012) define inertia as 'attachment to, and persistence of, existing behavioural patterns (i.e., the status quo), even if there are better alternatives or incentives to change' (p. 24). According to the status quo bias (SQB), humans are biased toward maintaining the status quo, either by doing nothing or by actively choosing the default (Samuelson and Zeckhauser, 1988). The SQB has often been considered as handling the real-world uncertainty decisions due to the people limited knowledge and hands-off experience of alternatives that may lead to stickiness to the current situation. SQB ultimately manifests itself externally as inertia. Individuals often strive to retain their settled usage habits (Zaltman and Wallendorf, 1983) and might demonstrate resistance 'either because it poses potential changes from a satisfactory status or because it conflicts with their belief structure' (Ram and Sheth, 1989, p. 6). Any change can possibly interrupt the psychological equilibrium of the people so

that they prefer to resist change rather than involve in a disturbing process of rearrangement (Ram, 1987). However, Polites and Karahanna (2012) assert that behavioural intention to continue the status quo and inertia are not equivalent, since low inertia does not necessarily imply that a user will adopt a new system. Because other reasons (e.g., value barriers, risk barriers, tradition barriers, and usage barrier) may trigger resistance. Thereby, users' level of inertia can moderate the relationship between behavioural beliefs such as reasons, attitudes, and adoption intentions (Polites and Karahanna, 2012). Consumers who perceive the RF or RA using a new system will differ in their attitude and intentions, depending on the level of inertia they have. With greater inertia, consumers may perceive benefits of using a new system and its superiority to the incumbent system, yet persist in continuing the current status either because this is what they have always done in before or it may be too stressful to change (Polites and Karahanna, 2012). By contrast, with lower inertia, consumers would be less resistant in using the new systems. Hence, we hypothesize that:

Hypothesis 6a. Inertia negatively moderates the relationship between users' reasons for and their attitude toward adoption, such that the positive effects of these reasons on attitude are weakened when inertia is higher.

Hypothesis 6b. Inertia negatively moderates the relationship between users' reasons for and their adoption intention, such that the positive effects of these reasons on adoption intention are weakened when inertia is higher.

Hypothesis 6c. Inertia positively moderates the relationship between users' reasons against and their attitude toward adoption, such that the negative effect of reasons against on attitude are strengthen when inertia is higher.

Hypothesis 6d. Inertia moderates the negative relationship between users' reasons against and their adoption intention, such that the negative effect of reasons against on adoption intention are strengthen when inertia is higher.

The main variables and their hypothesized relationships are presented in Figure 1.

Insert Figure 1 here

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3. Methodology

3.1. Measurements and Questionnaire Development

To ensure our variables' validity, confirmed measurement scales were adopted from previous studies. Adoption intention was measured with three items based on Mathieson (1991), such as: 'I plan to use ODSP in the future'. Attitude toward the adoption of on-demand service platforms was assessed with three items based on Ajzen (1991), with a sample item of 'Generally, using ODSPs is a good idea'. PESA was measured with four items (e.g. 'There are enough safeguards in the platform environment to make me feel comfortable using them for personal transaction') adapted from McKnight et al. (2002). Three Items of inertia (e.g. 'I generally consider the change as a negative thing') were adapted from Mani and Chouk (2018). We measured all items based on five-point Likert scales, ranging from strongly disagree (1) to strongly agree (5). All the measures are presented in Appendix 1.

BRT proposes that reasons are contextualized to the specific system and behaviour under investigation (Westaby, 2005). Therefore, we followed Claudy et al. (2015) to elicit context-specific reasons through an exploratory qualitative research. We collected qualitative data via (1) in-depth interviews with on-demand service platform professionals and practitioners, (2) focus group of prospective users, and (3) expert panel review.

First, we invited 12 on-demand service platform professionals and practitioners with more than 3 years' experience as founders, product managers and operational staffs for in-depth interviews. All the interviewees are involved in on-demand platforms in different roles, and thus, their different backgrounds would more likely ensure diverse insights about reasons for and against using ODSPs. We, then configured a focus group with 10 prospective users to identify possible reasons. The group was gender-balanced, consisted of diverse age groups, with different socio-demographic and cultural backgrounds. Throughout the in-depth interviews and focus group, the participants were asked to peruse the primary list of items extracted from the literature and identify irrelevant ones. They were also encouraged to suggest additional positive and negative reasons for using on-demand platform services. Influential factors for adopting or resisting digital platforms have been marginally touted in the literature, and thus, our qualitative research should be conducted to identify the 'context-based' attributes that are salient to ODSP users. To prepare the primary list, we summarised the discussed related factors in literature as digital platform adoption enablers and inhibitors, presented in Appendix 2. Through the course of the interviews, we found four items (improving local environment, enjoyment, prestige and social recognition) were irrelevant and thus excluded. Instead, interviewees proposed different items, such as selecting based on reputations and other users' feedback, getting the job done with value for money, ordering customized services, choosing and ordering several services concurrently, providing same-day and next day services, online monitoring the progress of the jobs, service guarantee, etc.

Finally, an expert panel examined the 32 items identified from in-depth interviews and focus group to evaluate the content validity (DeVellis, 2003). The expert panel was constituted of 3 academics and 3 senior industry professionals active in the digital platforms domain. We requested the panellists to carefully examine and review the applicability, representativeness, and clarity of the reasons and to provide feedback on wording and note if any reasons were missing. The expert panel did not propose any new reasons, indicating that the list reasons for/against adopting ODSPs was reasonably comprehensive. The experts suggested some wording changes to the reason items. We considered most of the phrasing recommendations to improve the clarity of the survey items.
We also included individual difference factors in our model to make sure that the empirical results are not due to covariance with other variables. Scholars propose incorporating education, gender, age, and expertise in the study as control variables given their significant effects in technology/service adoption decisions (Venkatesh et al., 2016). On-demand platform provider's reputation is also identified as a strong aspect influencing consumers' trust in the provider (Pavlou and Fygenson, 2006).

3.2. Data Collection and Sample Characteristics

A web-based survey was developed to empirically test the hypotheses of the theoretical framework. The results of the pilot study of 35 respondents did not reveal any inconvenience or ambiguity in the procedure. We considered Podsakoff et al.'s (2003) propositions to apply some procedural remedies for decreasing potential common method bias. For instance, on the questionnaire's cover page, we expressed that data will remain confidential, the results of this study are only for academic purposes, and the respondents' information would be anonymous. We approached UK based Facebook market research groups with totally 11.6 K members to reach the potential or prospective ODSPs users. These groups are originally formed for doing market research amongst UK potential customers as a focus group and the members expect remuneration for sharing their thoughts about products, services and companies. The Facebook Message System is used to randomly send the questionnaire, along with a covering letter for describing the research purpose and information privacy. As this study intends to understand the prospective cognition and reasoning about using an ODSP, participants were provided with a short description to establish a common understanding of what we mean by on-demand service platform. After reading the instructions on ODSP and providing some well-known examples (i.e., Uber, Just Eats, Deliveroo, TaskRabbit), respondents answered questions regarding both reasons for and reasons against resistance to use ODSP. We asked them to consider a service platform of their choice and answer the questionnaire accordingly. To incentivise the market research group members for participating, a £5 voucher was given for each completed questionnaire. Also, respondents would have a chance to win a £150 gift in a lucky draw if they responded the questionnaire within 2 weeks. Totally, 3,000 members of market research communities received our invitation and we collected 581 responses

during a four-week online survey. Consequently, about two-tenth of persons contacted agreed to participate in this survey, resulting in a fair response rate (19.4%), and a total of 523 correctly completed questionnaires were finally analysed (58 responses with at least one incorrect answer to the 'attention trap' questions were discarded). To assess the nonresponse bias (Armstronga & Overton, 1977), we compared the early and late respondents, which is, respondents who replied during the first week and those who replied during the last week. We performed a T-tests on the two groups, and the results did not show a significant difference in terms of demographic specifications and their intention to adopt an ODSP.

Forty-five percent of respondents were women and 55% were men. The majority of the respondents were 31–40 years old (38.6%) and 21–30 years old (38.1%), whereas the remaining percentage (23.3%) comprised 20 years old and below, 41–50 years old and over 51 years old. 11% of contributors have no diploma, 17% have a college degree, 38% have an undergraduate degree, and 25% have a postgraduate degree, the remaining 9% prefer not to say about their education.

4. Data Analysis and Findings

4.1. Exploratory Factor Analysis (EFA)

We conducted EFA based on principal axis factoring with a direct oblique rotation to apprehend the reasons for and reasons against adopting on-demand service platform. We adopted the cut-off points with a 0.4 factor loading value and 1.0 eigenvalue to conclude the number of factors and items (Hair et al., 2010). Five items were below the cut-off points and removed including: choosing and ordering several services concurrently, accessing to several professional service providers, customizing requested services, compatibility with lifestyle, and earning respect from others. Accordingly, the RF and RA adopting ODSP were underlaid respecting to four and five factors covering 32 items that accounted for 75.87% of the total variance. We labelled the four factors of RF as: Financial benefits, Flexibility, ODSP application superior functionality, ODSP special services, and the labelled the five RA factors as: Perceived complexity, Platform application security concerns, Service provider performance ambiguity, Service provider trustworthiness issues, and Financial concerns (Table 1 and Figure 2). The calculated Cronbach's alpha (Nunnally, 1978) for all of the factors were greater than 0.7.

Insert Figure 2 here

Insert Table 1 here

4.2. Model Specification and Testing

To test both measurement and structural models, we used SmartPLS Version 3.2.8 (Ringle et al., 2015). Partial least squares (PLS) is a component-based structural equation modelling that allows simultaneously examine different path between several independent and dependent variables (Gefen et al., 2011; Lowry and Gaskin, 2014; Ringle et al., 2012). Hair et al. (2016) propose a two-step method for PLS analyses, wherein we first tested the measurement model and then in the second step we evaluated the structural model.

We first examined the measurement model to ensure both convergent and discriminant validity. Convergent validity indicates the extent to which the measurement items can measure the underlying theoretical construct, while discriminant validity approves that two constructs empirically measures

different things (Fornell and Larcker, 1981). Our model convergent validity was built by meeting three criteria (e.g., Gefen and Straub, 2005; Bhattacherjee and Premkumar, 2004). First, each item loaded substantially on its related constructs, and none of the items loaded on their construct below the cut-off value of 0.5 (see Table 1 and Appendix 1). Second, the Cronbach's alpha and composite reliability of all constructs were over 0.70 (Fornell and Larcker, 1981; Nunnally, 1978). Third, each construct's average variance extracted (AVE) was greater than the cut-off value of 0.50, demonstrating that the variance described by respective constructs was more than 50 percent (Bagozzi and Yi, 1988). Discriminant validity was established by the Fornell–Larcker (1981) test: the squared values of construct correlations were lower than the AVE value for each study construct (Table 2).

Insert Table 2 here

We also applied a fairly new measure for assessing discriminant validity introduced by Henseler et al. (2015): the heterotrait-monotrait (HTMT) ratio of correlations. It is measured as "the average of the heterotrait-heteromethod correlations relative to the average of the monotrait-heteromethod correlations" (Henseler et al., 2015, p. 121). The HTMT values should be lower than 0.90, to approve the discriminant validity (Hair et al., 2016). The HTMT ratios are reported in Table 3 and all values are below the cut-off point of 0.90. Thus, according to both methods, the discriminant validity has been established.

Insert Table 3 here

Following Westaby (2005) and Claudy et al. (2015), in addition to examining the distinct effects of each reason on attitude and intention, we bundled reasons to RA and RF higher-order constructs (HOC). Establishing RA and RF as second-order constructs and building a higher-order model assists us in two ways: 1) reducing the number of relationships in our path model, thus, making it more parsimonious and easier to grasp (Hair et al., 2016); 2) overcoming the bandwidth-fidelity dilemma, by increasing the bandwidth of information covered through embracing HOC (Hair et al., 2017), while simultaneously including lower-order constructs to cover more concrete traits of HOC and keep the acceptable degree of precision in measurement (fidelity) (Sarstedt et al., 2019; Ones and Viswesvaran, 1996). Two second-order formative constructs representing RF and RA were formed using a two-step approach (Hair et al., 2016). Such that in the first step, the repeated indicator approach was applied to attain the latent variable scores for the first-order constructs. In the second step, the latent variable scores serve as indicators of higher-order constructs to test the structural models. We calculated the Variance Inflation Factor (VIF) to test if the two formative variables (i.e., RF and RA) were not highly correlated, (Petter et al., 2007). The results indicated that the VIF value for formative variables was less than 5, indicating that multicollinearity was not an issue for these constructs (Hair et al., 2016). In addition, we examined the significance of dimension weights to determine the relative contribution of items to the formative construct (Chin et al. 2003). All dimensions were significant at $p < 0.001$, indicating the significance of each first-order construct in forming the RF and RA constructs. Thus, results indicate our measures have good psychometric properties.

Next, SmartPLS Version 3.2.8 (Ringle et al. 2015) was also used to assess our structural model. Path coefficients, R-squared values, and significance in the main effects of the structural model and summary of all results are shown in Figures 3 and Table 4.

Insert Figure 3 here

Insert Table 4 here

In PLS, the coefficient of determination (R2) values are used to represent the explained variance of dependent variables (here attitude and intention), and the cross-validated redundancy indexes (Q2) are calculated to test the predictive relevance (Hair et al., 2016). The research model explained 54.8 percent of the variance (R2) in attitude toward adoption and 49.3 percent for adoption intention variance. The Q2 of 0.523 for attitude and 0.472 for intention, which were greater than 0, implied that the model has predictive relevance (Chin, 1998). In addition, we used a fit index of standardized root mean square residual (SRMR) for our composite factor model (Henseler et al., 2015). Assuming that the SRMR was below 0.08, the good fit of the model was confirmed (SRMR = 0.078).

Table 4 presents our path model analysis results predicting attitude and intention towards ODSPs. The results in model I, which examines the distinct influence of reasons, indicate that all of the reasons for and against significantly impact attitude. Among RF, financial benefit and flexibility and among RA, perceived complexity, service provider trustworthiness issues, and financial concerns have more salient effects on attitude. Our findings of Model I also show that among RF, only financial benefits and flexibility have a significant impact on intention, while all of RA negatively affects intention. Among RA, financial concerns and perceived complexity have greater negative impacts on adoption intention. The results of model II indicate that RF (H1a: β= 0.107, $p<0.01$) and RA (H1b: β= -0.301, $p<0.001$) have significant effects on consumers' attitude toward adoption of on-demand service platforms, thus, H1a and H1b are supported. While the results reveal that RF (H2a: β=0.068, $p>0.05$) do not have an influential direct effect on adoption intention, the relationship between intention and RA is negative and significant (H2b: β= -0.165, $p<0.01$). As we expected, RA negatively biases RF and the relationship is significant (H3a: β = -0.408, $p<0.001$). While H3b is not supported (β=0.043, $p>0.05$), the supporting of H3c indicates that RA negatively moderates the relationship between RF and adoption intention (H3c: β = -0.093, $p<0.05$).

Consistent with prior studies, attitude has significant positive effect on adoption intention (β = 0.184, $p < .01$), hence, supporting H4. H5a, H5b are supported and show that PESA positively moderates the relationship between RF, attitude, and intention. Also, supporting H5c, and H5d indicate that PESA negatively moderates the relationship between RA, attitude, and intention (H5a: β = 0.108, $p<0.05$; H5b: β = -0.129, $p<0.01$; H5c: β = 0.16, $p<0.01$; H5d: β = -0.179, $p<0.01$). Moreover, H6a, H6b, and H6d are supported: inertia negatively moderates the relation between RF and attitude and positively moderates the relation between RA, attitude and intention (H6a: β = -0.146, $p<0.01$; H6b: β = 0.107, $p<0.05$; H5d: β = 0.117, $p<0.05$). However, we did not find a moderating effect of inertia on the relationship between RF and intention (H5c: β = -0.067, $p>0.05$).

Although we did not hypothesize, the results reveal that PESA and inertia have significant direct effects on consumers' attitude and intentions towards adopting ODSP. Furthermore, only one of the control variables (i.e. gender) was insignificant for adoption intention. Age, education, expertise, and ODSP reputation have significant effects on intention.

5. Discussion and Implications

5.1. Discussion of Key Findings

This study seeks to examine the role of reasons in explaining pro/anti adoption behaviour of ODSPs. There are several important findings from this study. Two sets of context-specific reasons (i.e. RF and RA) were found to have significant impacts on attitude and intention towards adopting ODSPs. Financial benefits, flexibility, ODSP application superior functionality, and ODSP special services are

important RF factors for adopting ODSPs. We also found perceived complexity, platform application security concerns, service provider performance ambiguity, service provider trustworthiness issues, and financial concerns as RA have substantial negative impacts on attitude and intention. Specifically, the results show that reasons (for and against the behaviour) predict attitude as a motivating factor, and RA contribute to the prediction of intention beyond that explained by attitude. However, the findings show that RF has no direct effect on intention and only indirectly through attitude influences consumers' behaviour. Furthermore, our findings indicate that RA have greater effects on both attitude and adoption intention. Among RF, financial benefit and flexibility are salient drivers for attitude and intention, while perceived complexity, as well as concerns about costs and service provider trustworthiness, are stronger determinants for adopting ODSPs.

Consistent with cumulative prospect theory and our expectation, the path analysis in the research model shows that RA has a stronger influence on consumers' adoption decisions than RF. This finding is in contrast with Claudy et al.'s (2015) results: in sharing economy, 'reasons for adoption have a stronger influence on consumers' adoption decisions than reasons against adoption' (p. 539). However, this contradiction is not surprising and is in line with BRT which posits that psychological routs or processes in behavioural decision-making can vary subject to the decision context. So that in this study context (on-demand services that often require offline interactions), consumers are more sensitive to inhibitors and loss averse. Another notable finding is that RA negatively influence RF and moderate their impacts on adoption intention.

We also found that PESA and inertia moderate the relation between reasons and outcomes of interest. The findings propose that PESA moderates the impacts of RF on attitude and intentions such that the effect of these relations become stronger when PESA is high, yet undermines their impacts on attitude and intentions when it is low. This means that consumers may be more hesitant to consider RF adoption in their behavioural decisions if there is a perceived lack of effective structural assurance in place. Fukuyama (1995) divides environments dichotomously between high-trust and low-trust, and Gefen and Pavlou (2006) argue that in low-trust contexts, people mainly rely on governance mechanisms and institutional arrangements to protect them and to intervene in case of conflicts. When such mechanisms are in place, the result is decreasing social uncertainty and a greater willingness to engage in social-economic exchanges like in ODSPs. The findings also confirm that PESA negatively moderates the relationship between RA, attitude, and intention, such that the negative effect of RA on attitude and adoption intention is weaker when PESA is higher.

In addition, the results suggest that inertia positively moderates the relation between RA, attitude, and intention to adoption. Such positive interaction implies that when a consumer's inertia is high, RA for adopting a new system play more significant roles in determining attitude and intention decisions. In other words, RA have greater influence on adoption behaviours when inertia is present. However, the findings suggest that inertia does not have a significant moderating role in the relation between RF, attitude, and intention.

5.2. Theoretical Implications

This study offers several important contributions by providing greater insight into cognition routes underpinning the adoption of on-demand service platforms. First, the main theoretical implication of this study is that we take a broader view of the salient reasons for adoption intentions than has been typically examined. Considering only favourable or unfavourable set of factors separately, as are often maintained in adoption or resistance research, may result in incomplete and disconnected knowledge (Cenfetelli and Schwarz, 2011), or as Benbasat and Zmud (2003) assert leads to 'error of exclusion'. Therefore, drawing on Westby's (2005) behavioural reasoning theory, we developed an integrated model to advance our understanding of underlying reasons motivate pro/anti adoption behaviour. Our findings of testing this model show that RA and RF can simultaneously and markedly explain consumer adoption decision. Results show that adoption attitude and intention are function of both RF and RA and consumers mutually evaluate these two reason sets to make their usage decisions.

Second, current paper contributes to the extant literature on ODSP and digital platforms in general where there is a lack of theoretically grounded and empirically validated models to understand consumers' adoption behaviours. Despite the enormous growth and increasing attention that ODSP attracts among practitioners and the general public, little research has been done to identify consumers' motivations and concerns of adopting and using these novel digital markets. To address this backdrop in literature, through a qualitative elicitation research, we explored prominent context-specific reasons, instead of broad belief constructs, as antecedents to the consumers' adoption or rejection decisions. Further, by empirically testing our context-specific model, we identified and examined different paths that consumers may follow in their adoption decision-making process.

Third, this study has implications for BRT by indicating that as an overarching theoretical framework BRT is valuable to improve our knowledge of consumers' motive to adopt or reasons to resist ODSPs. Furthermore, following Westaby's (2005, p. 117) call 'to examine the moderating conditions in BRT', we included external factors (here PESA and inertia) in our model, which play moderating role in affecting the relationships between reasons and consumers' attitude and intentions to adopt ODSPs. This study provides a fresh understanding of how consumers' motives and concerns influence due to the presence or lack of institutional settings and structural assurances to boost trust and reduce uncertainty in the platforms market environment. Drawing on the theoretical perspective of SQB, this study contributes to the literature by revealing how consumers' beliefs regarding reasons, attitude or intention can be subject to users' level of inertia. We showed that an inert consumer of incumbent systems biases her adoption decisions by neglecting or undermining RF, as well as strengthening RA to justify her decision on resisting using new systems to avoid suffering cognitive dissonance (Polites and Karahanna, 2012).

Finally, according to Westaby's (2005) suggestion and by adapting the cumulative prospect theory, this study introduces a novel theoretical perspective given the diminishing sensitivity and loss aversion of consumers and extends BRT by adding the effect of bias of reasons against on reasons for adoption. Our study in line with the work of Cenfetelli and Schwarz (2011) confirms that RA can bias RF. This suggests that there is a meaningful tendency of the negatives to be stronger than the positives. However, while Cenfetelli and Schwarz (2011) noticed partial support for this relation, our findings suggest that the negative effect of RA on RF is strong.

5.3. Practical Implications

Our findings provide better insights for practitioners of ODSP to enhance their understanding of consumers' decision-making rationality to avoid potential failure. First, our study explores salient context-specific factors in adopting ODSP. The results show that it is essential for ODSP providers to emphasize and strengthen the RF adoption like financial benefits, flexibility, ODSP application superior functionality, and ODSP special services. Moreover, results suggest that ODSP practitioners should reinforce on-demand services against inhibitor factors such as perceived complexity, application security concerns, concerns related to service providers, and financial issues. The strong impacts of RA on RF indicate that prospective users are very sensitive to negatives and this may bias their evaluations about RF. Thus, ODSP providers should not limit themselves to increasing RF or making them better, but they should commit more resources to resolve the risks and concerns. Particularly, our findings illustrate that although many consumers perceive financial benefits and flexibility of ODSPs and choose to adopt these novel systems, managers should address consumers' concerns regarding costs, complexity of using these systems and service providers' trustworthiness. For instance, platform managers could employ governance policies to decrease information asymmetry between consumers and service providers by using transparent pricing mechanisms, guaranties, reliable feedback and reputation systems or establishing counselling departments to help consumers to resolve their uncertainties.

This study recommends to the ODSP providers that while it is important to focus on reasons, PESA and inertia are two effective means that can modify the effects of reasons on consumers' adoption decisions. The significant interaction effects of inertia on the relations between RA, attitudes, and intentions posit

that the ODSP managers should employ proper policies like upstream interventions for breaking and modifying inertia. Providing incentives, contextual support or making a more conducive environment to practice new behaviour will help to reduce the concerns, and encourage attitude change and consumers' intention to adopt the new system (Polites and Karahanna, 2012). The significant interaction effects of PESA suggest that when PESA is high, consumers are more likely to consider RF to adopt ODSPs. Therefore, if on-demand service platform providers operate in a low trust environment, they should more highlight platform's benefits, commit more resources on reducing concerns particularly in transactional (service providers) and local (platform) levels. The significant effects of PESA demonstrates that government, Internet and market policymakers should design and institutionalize structural assurance mechanisms to mitigate risks and uncertainties for the entire platform's market. The existence of more robust structural assurances like solid, highly specialised legal bonds or liability insurance could help to make reliable environment and build less difficult mandates for ODSP practitioners to embark upon, thereby contributing to the prosperity of digital platforms.

6. Conclusion

Digital platform such as those for sourcing and providing on-demand services have gained centrality in today's service economy landscape. However, there has been a lack of understanding of antecedents and cognition routes underpinning consumers' pro/anti adoption decisions. Grounded on behavioural reasoning theory, this study explored context-specific drivers and inhibitors of using ODSPs and examined their impacts on consumers' adoption intention in a single framework. Behavioural reasoning theory as an overarching theoretical lens guided our model development and further explaining consumers' behaviours simultaneously investigating reasons for and against adoption ODSPs. This study is an initial attempt that developed a theory-driven, data-grounded model to explain consumers' adopting ODSP as a new form of the digital economy. The proposed model sheds light on different logical processes and variances in consumers' behavioural decisions depending on the context in using ODSP over and above that of traditional models. We move further than the classic BRT by incorporating the role of SQB and institution-based trust mechanisms in adopting on-demand platforms and highlight the moderating role of PESA and inertia in the relationship of reasons and consumers' motives and intentions. The linkages in BRT are furthered extended and showed that the significant negative effects of RA could impose bias on RF and influence consumers' attitude and adoption intention. Overall, we believe that our study provides a well-defined foundation to help understand, assess, and improve the consumers' attitudes and intentions who might use on-demand service platforms.

6.1. Limitation and Future Research

The primary interest of our study was to examine and extend the BRT as a selected theoretical perspective to understand the consumers' adoption intention in the ODSP context. While our work contributed toward digital platform literature, it has some limitations to be addressed in future research. First, we considered on-demand service platforms as the selected type to be surveyed, due to its importance in micro-entrepreneurship facilitation (Lehdonvirta et al., 2019). Other types of digital platforms such as capital platforms or social mission platforms (for example civic crowdfunding platforms) are worthy to be studied in future research. Second, as influential factors, we incorporated PESA and inertia, and we investigated their moderator effects based on the literature. Future research could be designed and followed by considering platform provider specifications such as brand and reputation, marketing policies and initiatives, and company credibility (Hajiheydari et al., 2018). Third, the results could be furthered tested in different populations with variant levels of expectations and diverse reasoning logic. Fourth, the results are relied on self-reporting measures, which might have caused common method bias. Future research could utilize research designs such as experimental techniques that would help address this issue. Future studies could also benefit from BRT configuration to identify determinants of actual adoption behaviour, and post-adoption user perception, where feasible. Finally, Germonprez and Hovorka (2013) claim that the potential benefits of network effects in a platform necessitate long-run consideration for reliably predicting its inception. Therefore, longitudinal studies in this field could be considered as a fruitful subject for future studies.

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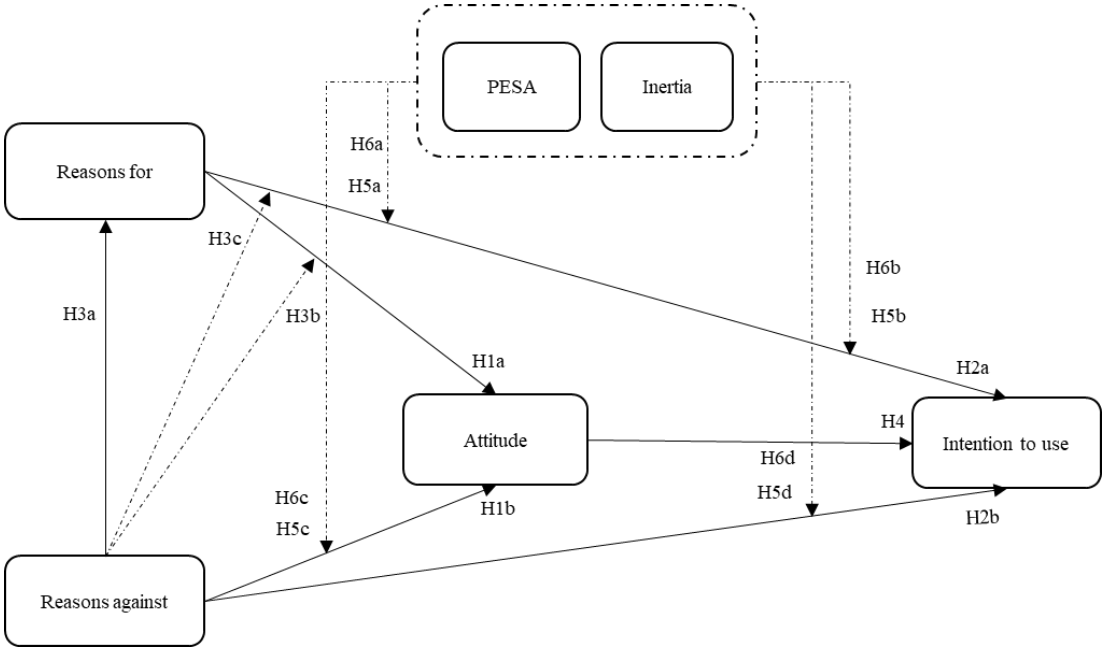

Figure1. The theoretical framework of this research

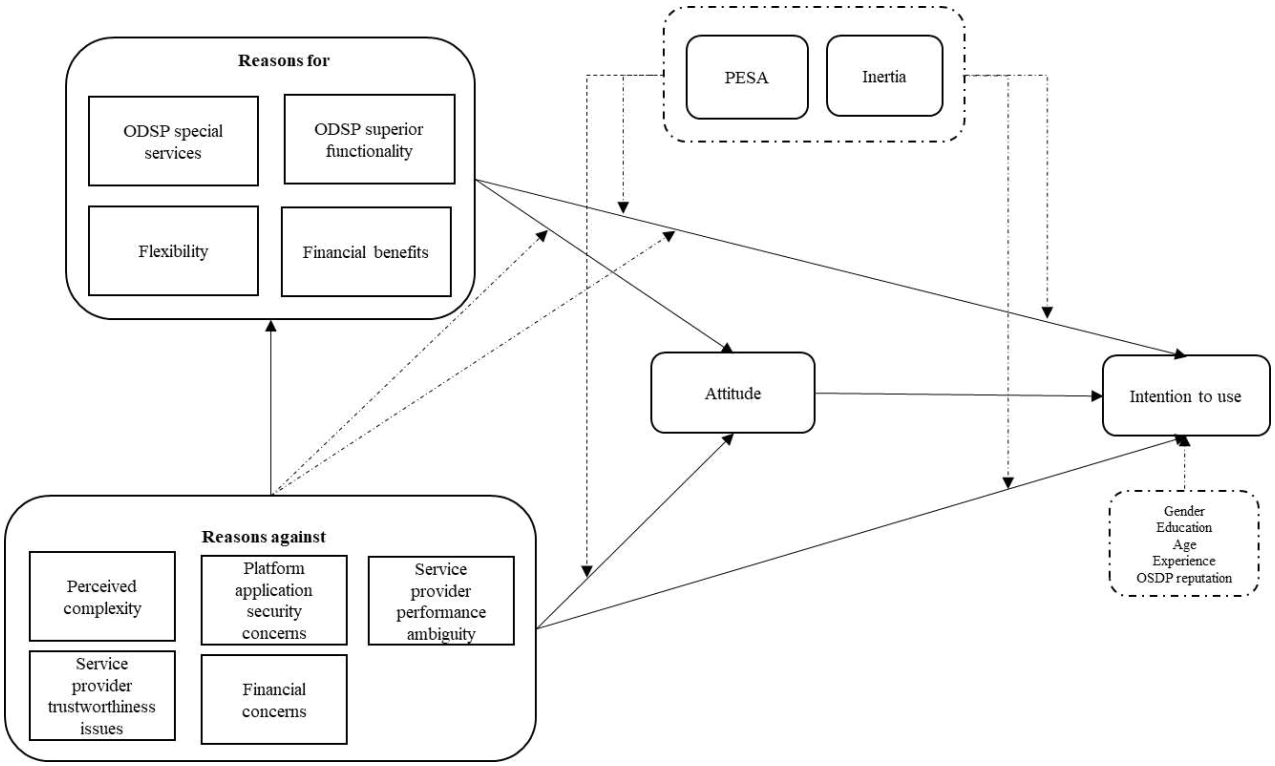

Figure 2. Context-specific reasons for and against of behavioural model

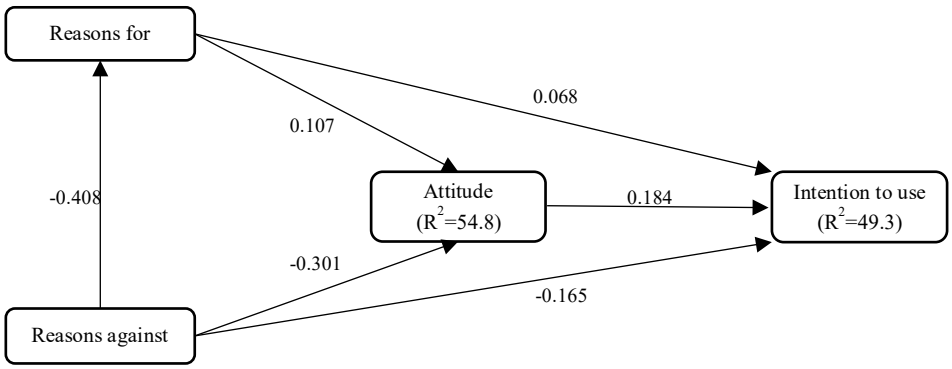

Figure 3. Structural model of main effects results

Table 1. Results of Exploratory Factor Analysis (EFA)

Factors	1	2	3	4	5	6	7	8	9
Factor 1: Perceived complexity									
1. Using [on-demand service platform] is not easy.	**0.869**	-0.011	-0.015	-0.028	0.024	0.055	-0.041	0.017	-0.073
2. Using [on-demand service platform] is complicated.	**0.907**	0.007	-0.005	0.005	0.011	-0.026	0.018	0.005	0.041
3. Using [on-demand service platform] is confusing.	**0.794**	0.013	0.048	0.009	0.011	-0.051	0.013	0.017	0.055
4. Using [on-demand service platform] needs a special skills and knowledge.	**0.849**	-0.006	-0.004	0.018	-0.024	0.026	0.008	-0.04	-0.043
Factor 2: Platform application security concerns									
1. Using [on-demand service platform] is not safe and secure.	0.005	**0.896**	-0.008	-0.015	0.008	0.019	-0.012	-0.011	-0.038
2. [On-demand service platform] may misuse customers' information.	-0.002	**0.9**	0.008	0.027	0.001	-0.01	0.009	0.011	0.044
Factor 3: Service provider performance ambiguity									
1. [On-demand service platform] quality of services may not be good.	0.038	-0.007	**0.921**	-0.045	0.00	-0.026	0.029	0.04	-0.058
2. [On-demand service platform] service providers are qualified to do their jobs®.	-0.026	0.012	**0.937**	-0.022	-0.015	0.007	-0.014	-0.025	0.038
3. [On-demand service platform] service providers might not accomplish requested services.	0.015	-0.008	**0.797**	0.104	0.025	0.024	-0.009	-0.028	0.023
Factor 4: Service provider trustworthiness issues									
1. [On-demand service platform] service providers may not be committed and keep promises.	0.01	0.023	0.026	**0.887**	-0.012	-0.026	-0.019	0.019	-0.021
2. [On-demand service platform] service providers may not be frank.	0.02	-0.03	-0.016	**0.963**	0.005	0.01	0.012	-0.005	-0.011
3. [On-demand service platform] service providers may not be trustworthy.	-0.015	0.026	0.009	**0.855**	0.024	-0.003	0.002	-0.01	0.002
Factor 5: Financial concerns (α = 0.890)									
1. Using [on-demand service platform] is costly.	0.062	-0.024	-0.026	0.035	**0.833**	-0.014	0.015	-0.022	0.047
2. [On-demand service platform] might charge extra cost.	0.045	0.012	-0.026	0.103	**0.709**	-0.006	-0.025	-0.013	0.062
3. [On-demand service platform] service providers may make false claims.	-0.055	0.01	0.01	-0.071	**0.838**	-0.019	-0.007	-0.021	-0.038
4. I have no bargaining power for determining the cost of services in [on-demand service platform].	-0.008	0.012	0.039	-0.026	**0.815**	0.024	0.01	0.042	-0.083
Factor 6: Financial benefits									
1. [On-demand service platform] represents good value for money.	-0.034	-0.03	0.03	0.00	-0.063	**0.847**	-0.012	-0.007	-0.029
2. I can receive a service with less cost while using the [on-demand service platform].	-0.046	0.019	-0.014	0.037	-0.029	**0.856**	0.039	-0.009	-0.019
3. I can find service providers with lower cost in [on-demand service platform].	0.041	-0.017	-0.028	-0.023	0.037	**0.838**	-0.012	-0.011	0.051
4. Searching and comparing the cost of services are easy in [on-demand service platform].	0.035	0.034	0.013	-0.022	0.029	**0.896**	-0.01	0.04	0.024
Factor 7: Flexibility									
1. Using [on-demand service platform] would save time when receiving professional services.	-0.017	-0.005	-0.059	-0.028	-0.034	0.1	**0.731**	-0.05	0.002
2. I can remotely order something to be done when using [on-demand service platform].	-0.033	-0.022	-0.018	0.049	-0.016	0.016	**0.786**	0.084	-0.033
3. I can register my order in [on-demand service platform] 24/7.	0.029	0.021	0.007	-0.045	0.05	-0.003	**0.848**	0.022	0.028
4. Using [on-demand service platform] is more convenient than the other options in receiving professional services.	0.00	-0.003	0.042	0.018	-0.019	-0.053	**0.906**	-0.04	0.023
Factor 8: ODSP application superior functionality									
1. I can select professional service providers based on other users' feedback in [on-demand service platform].	-0.057	0.007	0.043	-0.05	-0.001	0.056	0.036	**0.788**	-0.03
2. Giving feedback about the quality of the service is easy in [on-demand service platform].	0.054	-0.004	-0.03	0.014	-0.025	-0.002	-0.058	**0.961**	0.021
3. Online monitoring of the job's progress is possible in [on-demand service platform].	-0.017	0.00	-0.013	0.027	0.018	-0.024	0.044	**0.834**	0.022
Factor 9: ODSP special services									
1. [On-demand service platform] provides service guarantee.	-0.05	0.001	0.06	-0.044	0.022	0.007	0.008	-0.004	**0.854**

2. [On-demand service platform] provides same-day and next day services.	0.031	0.082	-0.039	-0.032	-0.071	-0.028	0.026	-0.004	**0.774**
3. [On-demand service platform] provides online customer service.	0.001	-0.085	-0.024	0.055	0.026	0.069	-0.004	0.035	**0.778**

Table 2. Confirmatory factor analysis (CFA) results

	CA	CR	AVE	1	2	3	4	5	6	7	8	9	10	11	12	13
Attitude	0.88	0.96	0.9	**0.95**												
OSS	0.87	0.92	0.79	0.47	**0.89**											
OASF	0.91	0.94	0.84	0.5	0.59	**0.92**										
FB	0.93	0.93	0.77	0.57	0.64	0.65	**0.88**									
FC	0.89	0.92	0.74	-0.52	-0.49	-0.52	-0.6	**0.86**								
Inertia	0.85	0.96	0.9	-0.6	-0.39	-0.41	-0.47	0.47	**0.95**							
Intention	0.89	0.97	0.92	0.75	0.49	0.52	0.6	-0.53	-0.66	**0.96**						
PESA	0.91	0.98	0.94	0.72	0.41	0.46	0.53	-0.48	-0.57	0.78	**0.97**					
PC	0.92	0.94	0.79	-0.6	-0.54	-0.55	-0.59	0.66	0.52	-0.6	-0.57	**0.89**				
SPPA	0.92	0.95	0.59	-0.56	-0.5	-0.48	-0.57	0.53	0.51	-0.61	-0.49	0.6	**0.92**			
PASC	0.89	0.95	0.55	-0.56	-0.39	-0.41	-0.46	0.44	0.46	-0.54	-0.48	0.46	0.44	**0.95**		
SPTI	0.94	0.94	0.85	-0.62	-0.56	-0.56	-0.66	0.64	0.49	-0.61	-0.51	0.69	0.68	0.49	**0.93**	
Flexibility	0.90	0.95	0.9	0.59	0.66	0.64	0.73	-0.6	-0.45	0.59	0.54	-0.67	-0.58	-0.47	-0.65	**0.87**

Note: OSS = ODSP special services; OASF = ODSP application superior functionality; FB = Financial benefit; FC = Financial concerns; Perceived effectiveness of structural assurance; PC = Perceived complexity; SPPA = Service provider performance ambiguity; PASC = Platform application security concerns; SPTI = Service provider trustworthiness issues

Table 3. HTMT ratios of the constructs

		1	2	3	4	5	6	7	8	9	10	11	12
1.	Attitude												
2.	OSS	0.52											
3.	OASF	0.54	0.67										
4.	FB	0.61	0.72	0.72									
5.	FC	0.57	0.56	0.57	0.67								
6.	Inertia	0.64	0.43	0.44	0.51	0.51							
7.	Intention	0.79	0.54	0.56	0.64	0.58	0.70						
8.	PESA	0.75	0.45	0.49	0.57	0.51	0.60	0.81					
9.	PC	0.65	0.61	0.60	0.65	0.74	0.56	0.64	0.60				
10.	SPPA	0.60	0.56	0.53	0.63	0.59	0.56	0.65	0.53	0.66			
11.	PASC	0.61	0.44	0.46	0.52	0.49	0.50	0.59	0.52	0.51	0.49		
12.	SPTI	0.67	0.63	0.61	0.72	0.71	0.52	0.65	0.54	0.75	0.74	0.54	
13.	Flexibility	0.64	0.75	0.71	0.81	0.67	0.48	0.63	0.58	0.74	0.65	0.52	0.72

Note: OSS = ODSP special services; OASF = ODSP application superior functionality; FB = Financial benefit; FC = Financial concerns; Perceived effectiveness of structural assurance; PC = Perceived complexity; SPPA = Service provider performance ambiguity; PASC = Platform application security concerns; SPTI = Service provider trustworthiness issues

Table 4. Detailed results of structural model

Variables	Attitude			Intention		
	Model I	Model II	Result	Model I	Model II	Result
Main effects of FOC						
FB	.471***		significant	.185**		significant
Flex	.263**		significant	.112*		significant
OASF	.165**		significant	.071		ns
OSS	.179**		significant	.043		ns
PC	-.356***		significant	-.213**		significant
PASC	-.212**		significant	-.182**		significant
SPPA	-.175**		significant	-.147*		significant
SPTI	-.281**		significant	-.109*		significant
FC	-.573***		significant	-.221**		significant
Main effects of HOC						
RF		.107*	H1a supported		.068	H2a not supported
RA		-.301***	H1b supported		-.165**	H2b supported
Attitude					.184**	H4 supported
Interaction terms						
RA × RF		.043	H3b not supported		.093*	H3c supported
PESA × RF		.108*	H5a supported		.16**	H5b supported
PESA × RA		-.129**	H5c supported		-.179**	H5d supported
Inertia × RF		-.146**	H6a supported		-.067	H6b not supported
Inertia × RA		.107*	H6c supported		.117*	H6d supported
Control						
Gender					.034	ns
Education					.103*	ps
Age					.087*	ps
Expertise					.105*	ps
ODSP reputation					.141*	ps

Note: FOC = First order constructs; HOC = Higher-order constructs; FB = Financial benefit; Flex = Flexibility; OASF = ODSP application superior functionality; OSS = ODSP special services; PC = Perceived complexity; PASC = Platform application security concerns; SPPA = Service provider performance ambiguity; SPTI = Service provider trustworthiness issues; FC = Financial concerns; ns = insignificant; ps = Partially significant; *p<0.05; **p<0.01; ***p<0.001

Appendix 1. Questionnaire items & the loadings

Construct	***Items***	***loading***
Adoption intention	1. I plan to use [on-demand service platform] in the future.	0.964
	2. My intention would be to use [on-demand service platform] rather than traditional methods for receiving the required services.	0.963
	3. To make my jobs done, I would use [on-demand service platform] rather than traditional methods.	0.943
Attitude toward ODSP	1. Generally, using [on-demand service platform] is a good idea.	0.95
	2. [On-demand service platform] has lot of benefits at work.	0.952
	3. [On-demand service platform] can offer a lot of advantages.	0.938
Inertia	1. I generally consider the change as a negative thing.	0.948
	2. I'd rather do the same old things than try new ones.	0.955
	3. In my opinion, prior technological systems were satisfactory so far.	0.936
PESA	1. There are enough safeguards in the platform environment to make me feel comfortable using them for personal transaction.	0.971
	2. I feel assured that legal and technological structures adequately protect me from problems on the platform environment.	0.974
	3. I feel confident that technological advances on the platform environment make it safe for me to do transaction there.	0.966
	4. In general, the platform environment is now a robust and safe context in which to do transaction.	0.954

Appendix 2. The primary list of on-demand service platform adoption and resistance factors

Reasons for using an ODSP		***Related literature***
Flexibility Perceived flexibility in receiving the service is a major antecedent to intention to use an ODSP.	I will use an ODSP because… • It's an easy way for me to conclude my transaction. • It knows about the needs of their customers. • It's versatile in addressing needs as they arise. • It can be adapted to meet a variety of needs.	Möhlmann, 2015; Yaraghi and Ravi, 2017
Enjoyment Enjoyment or perceived pleasure has been regarded as an important factor that affect users' satisfaction and using intention.	I will use an ODSP because… • I think using ODSP is an experience of pleasure. • I feel the process of using ODSP is enjoyable. • I think using ODSP is fun.	Hamri et al., 2016; Barnes and Mattsson, 2017
Financial benefits The Users' perception of cost-saving benefits through using the ODSP is a fundamental adoption motivation.	I will use an ODSP because… • It's a way for saving money. • It's a low-cost option. • It's an economical alternative to traditional service provision.	Barnes and Mattsson, 2017; Zhang et al., 2019
Environmental benefits The users' perceptions of environmental (sustainability) benefits motivate them for using digital platforms	I will use an ODSP because… • It's considered as a contribution to the environment. • It helps my local environment with the sustainability purpose. • It helps saving natural resources. • It's environmentally friendly.	Hamri et al., 2016; Barnes and Mattsson, 2017; Roos and Hahn, 2017
Social recognition The social norms and gaining reputation among likeminded people influence the users' motivation in using ODSPs.	I will use an ODSP because… • It improves my image within the community. • I gain recognition from the community by using ODSP. • I would earn respect from others by using ODSP. • People who use ODSPs have more prestige than those who do not. • People who are important to me think that I should use OSDPs. • People who influence my behaviour encourage me to use ODSP. • Most people who are important to me use ODSPs.	Hamri et al., 2016; Roos and Hahn, 2017
Reasons against using an ODSP		***Related literature***
Risk barrier Perceived security risk and concerns about the possibility of losing control over private and personal data hinder using technology.	I will not use an ODSP because… • I am worried about the security of my personal data. • I am worried about liability in case of unfulfilled services. • I have no idea how qualified the service provides are.	Cluady et al., 2015; Bielefeldt et al., 2017
Functionality barrier Users' uncertainty about the result of using ODSP is also negatively related to their intention.	I will not use an ODSP because… • I am concerned that OSDP would not provide the level of services I expect. • I am concerned that the provided service may not meet my expected level of service. • I am unsure if the service would match my expectations in reality.	Cluady et al., 2015; Spindeldreher et al., 2018
Value barrier Users' perception about the economic cost of using ODSP is related to their resistance.	I will not use an ODSP because… • I feel it is more expensive than the traditional service providers are. • It is costly. • It might charge extra cost.	Bielefeldt et al., 2017

	• I have no bargaining power for determining the cost of services.	
Perceived complexity If users perceive ODSP as difficult to understand and use, more likely incline to resist against its adoption.	I will not use an ODSP because… • I feel using an ODSP is not easy. • I think using an ODSP is complicated. • I feel using an ODSP is confusing. • I feel using an ODSP needs special skills and knowledge.	Bielefeldt et al., 2017; Spindeldreher et al., 2018