An Integrated Model To Predict The Intention To Use Delivery Robot For Last-Mile Delivery: A Structural Equation Modeling Approach

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Abstract : Considering the rise in the online shopping rate, last-mile delivery has become one of the most important challenges for logistics service providers. In contrast to traditional delivery methods, new methods have been proposed, including sidewalk autonomous delivery robots (SADRs). The present study aims to investigate the factors affecting the adoption of SADRs by online shoppers in Iran. To this end, a model was proposed based on the diffusion of innovation theory (DOI) and technology acceptance model (TAM) by adding two variables, namely personal innovativeness and perceived risk. A total of 287 respondents were surveyed using an online questionnaire, and the partial least squares structural equation modeling (PLS-SEM) was employed for modeling. The results indicated that relative advantage, compatibility, complexity, and observability impacted consumers' attitude toward using delivery robot; however, no significant relationship was found between trialability and attitude. Also, relative advantage and personal innovativeness had a positive and perceived risk had a negative impact on consumers' intention to use delivery robot. The findings of the present study provide significant theoretical and practical contributions to logistics service providers and marketers.
Keywords: Autonomous delivery robot, Last-mile delivery, Diffusion of innovation, Technology acceptance model, Adoption behavior, PLS-SEM

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1. Introduction

In light of advancements in internet-related technologies and instruments, online shopping is considerably growing across the world every year. According to the World Bank, the penetration rate of Iranian online shoppers reached 26% in 2018 (Eqtesad, 2019). The Iran Credit Card Payment Network (SHAPARAK) statistics suggest that the total online interaction amount was 1380,000 billion Rials (IRR) in 2017 (Itiran, 2018), reaching nearly 1456,000 billion IRR under 774 million transactions in 2018. On the other hand, the total cash on delivery was 350,000 billion IRR under over 50 million transactions. Thus, considering the rise in the online shopping rate, same-day delivery has become an essential topic in transportation and environmental debates.

Today, new methods are under testing or operation for last-mile delivery (Joerss, Schröder, Neuhaus, Klink, & Mann, 2016; Lebeau, Macharis, & Van Mierlo, 2016; Lee, Chen, Gillai, & Rammohan, 2016; Mangiaracina, Perego, Seghezzi, & Tumino, 2019; Ranieri, Digiesi, Silvestri, & Roccotelli, 2018; Schroder et al., 2018), including sidewalk autonomous delivery robots (SADRs) that deliver small-sized products, such as food, grocery, and flowers, in some places across the world (Hoffmann & Prause, 2018). Different companies, including Amazon, Starship, FedEx, and Marble, are testing and employing such robots in some thinly-crowded places, such as campuses. The specifications of such small-sized robots vary, depending on their manufacturers; however, they have almost the same characteristics. For example, Starship electric-powered robots weigh less than 45 kg and can deliver products in a radius of up to 6 km through sidewalks. These self-driving robots can carry a weight of up to 10 kg at a maximum speed of 16 km/h. Furthermore, they feature radars, GPS, cameras, and ultrasonic sensors to distinguish humans from obstacles. Online shoppers can instantly locate the robot by installing the required application. The robot is locked during the travel, and the user is informed of robot arrival by the application. Finally, the robot is unlocked using a specific code provided to the user on the application (brilliantinfosys, 2018; Hoffmann & Prause, 2018; Newatlas, 2016; Prause & Boevsky, 2018; Starship, 2014).

The use of such robots as a new generation of delivery methods can provide various advantages (Hoffmann & Prause, 2018). Since these robots are electrically powered, they emit very smaller CO_2 contents than traditional methods. Also, the cost of this method is estimated to be up to 15 times as lower as that of traditional methods. Delivery robots enhance the efficiency of the delivery process. For example, they offer customers a delivery window of 15-30 minutes. Furthermore, since robots do not need to rest (unlike humans), they can be employed 24/7, even during off-peak hours (Hoffmann & Prause, 2018; Kunze, 2016; Lee et al., 2016; Prause & Boevsky, 2018; Robotics, 2016). In addition to the mentioned advantages, delivery robots may perform more effectively than traditional methods in crises. For example, they can be very efficient and help both customers and vendors in the COVID-19 crisis; individuals are no longer required to deliver products, and customers do not need to take the risk of leaving their homes and can safely make their purchases.

The present study investigated the factors influencing the adoption of delivery robots by Iranian online shoppers. To this end, a model was proposed based on the constructs of the diffusion of innovation theory (DOI) (Rogers, 1983) and the technology acceptance model (TAM) (Davis, 1985). Also, perceived risk and personal innovativeness were incorporated into the model, evaluating their impacts on behavioral intention. The remainder of the present study is organized as follows: Section 2 reviews the literature and integrates the mentioned theories; Section 3 describes the proposed model and provides hypotheses; Section 4 describes the questionnaire design and data collection procedure; Section 5 provides the structural equation model results; and, Section 6 discusses the results and concludes the work.

2. Literature review

2.1. Delivery robot-related studies

Various studies have been dedicated to the introduction, advantages, disadvantages, routing problems, and other aspects of delivery robots (Boysen, Fedtke, & Schwerdfeger, 2020; Deng, Amirjamshidi, & Roorda, 2020; Hoffmann & Prause, 2018; Lee et al., 2016). For example, Simoni, Kutanoglu, and Claudel (2020) investigated the possibility of implementing an integrated truck-robot system. Boysen, Schwerdfeger, and Weidinger (2018) programmed a procedure to deliver products in a timely manner by using truck-based autonomous delivery robots. Jennings and Figliozzi (2019) found that delivery robots could reduce the time and cost of delivery, as compared to traditional methods. Figliozzi and Jennings (2020) calculated and compared the pollution and energy consumption of SADRs and road autonomous delivery robots (RADRs).

Unlike delivery robots, drone delivery has been subject to several studies as a delivery alternative. Ramadan, Farah, and Mrad (2017) proposed a model composed of drone's service performance, drone personification, safety risk, and privacy risk to investigate the adoption of drone delivery among customers. Yoo, Yu, and Jung (2018) found that performance risk, privacy risk, complexity, and the relative advantages of environmental friendliness and speed impacted the intention of customers to use drone delivery. The findings differed between different residence regions of the respondents. Kim and Hwang (2020) integrated the theory of planned behavior (TPB) and the norm activation model (NAM) to examine factors impacting the adoption of drone delivery for food services. Hwang, Lee, and Kim (2019) found that perceived innovativeness had a positive and significant impact on attitude and intention in South Korea. A number of studies evaluated the risks of utilizing drone delivery in recent years. For example, Khan, Tausif, and Javed Malik (2019) reported privacy as the most important concern of Pakistani consumers about drone delivery. However, since delivery robots are a new idea, recent studies have not comprehensively covered their entire aspects. The adoption of delivery robots as a method of receiving the online-purchased products by shoppers has been subject to few studies (Joerss et al., 2016; Kapser & Abdelrahman, 2020). To the best of our knowledge, Kapser and Abdelrahman (2020) were the first that proposed a model based on the Unified Theory of Acceptance and Use of Technology (UTAUT2) in Germany. They evaluated the impacts of the UTAUT2 constructs on the intentions of shoppers to use delivery robots by using the structural equation model and surveying 501 German shoppers. It was found that performance expectancy, social influence, facilitating conditions, and hedonic motivation had a positive and price sensitivity and perceived risk had a negative effect on behavioral intention. Kapser, Abdelrahman, and Bernecker (2021) used gender as a moderator variable. They added innovativeness and trust in technology to the research model and concluded that price sensitivity, performance expectancy, and trust in technology impact the intention to use delivery robots. However, social influence, hedonic motivation, and perceived risk are significant only for women. Almost in the same context, Pani, Mishra, Golias, and Figliozzi (2020) employed latent class analysis (LCA) and identified six consumer segments. They investigated factors influencing willingness to pay (WTP) during the COVID-19 pandemic.

Since a limited number of studies have been conducted in this field, it is required to investigate the use of delivery robots from the perspective of online shoppers. To fill this gap, by integrating DOI and TAM and incorporating perceived risk and personal innovativeness, the present study contributes to understanding the intentions of Iranian online shoppers to use this method. To the best of the authors' knowledge, no studies had been conducted with the approach of integrating the DOI and TAM.

2.2. Integrating the DOI and TAM

The DOI (Rogers, 1983) and TAM (Davis, 1985) are among the oldest and most commonly used theories for describing how new technologies, products, or services are accepted by individuals (Di Pietro, Mugion, Mattia, Renzi, & Toni, 2015; Hanafizadeh, Keating, & Khedmatgozar, 2014). According to DOI, five key factors affect the intention of individuals to use new technologies, including relative advantage, compatibility, complexity, observability, and trialability, which are defined as "the advantage of a new technology over the previous one," "the consistency of the new technology with the requirements, lifestyles, and experience of individuals," "the difficulty of learning and using the new technology," "the observability of the benefits and outcomes of using the new technology," and "the trialability of the new technology before use," respectively (Rogers, 1983). It was suitable to employ the DOI theory in the present study since the use of delivery robots as a method of delivering products is a new, innovative approach in this field. This approach has been adopted in related studies, including automated parcel stations, drone delivery, and automated vehicles (Yoo et al., 2018; Yuen, Wang, Ng, & Wong, 2018; Yuen, Wong, Ma, & Wang, 2020).

In TAM, two key variables affect the attitude of individuals toward using technology, including perceived usefulness and perceived ease of use (Vijayasarathy, 2004). A comparison of DOI and TAM suggests that perceived usefulness and perceived ease of use in the TAM are very similar to relative advantage and complexity in the DOI theory (Moore & Benbasat, 1991; Wu & Wang, 2005). Previous studies have shown that the integration of these two theories can lead to a stronger model. Hence, DOI and TAM can complement each other (L. D. Chen, Gillenson, & Sherrell, 2002; Davis, 1989; Di Pietro et al., 2015; Rogers, 1995; Wu & Wang, 2005). Also, many studies investigated the intentions of individuals to use new technologies by integrating these two theories (Min, So, & Jeong, 2019; Tsai & Tiwasing, 2021; Yaprak, Kılıç, & Okumuş, 2021; Yoo et al., 2018).

3. Proposed model and hypotheses

As mentioned, the present study investigates the intentions of online shoppers to use delivery robots by integrating DOI and TAM. Relative advantage and complexity in DOI were used to replace perceived usefulness and perceived ease of use (with the opposite sign) in TAM. Also, the impacts of relative advantage, complexity, and the remaining constructs of DOI on the intentions of individuals were studied indirectly through attitude. On the other hand, the direct impacts of the added constructs (i.e., personal innovativeness and perceived risk) on the intention were considered. Fig. 1 illustrates the structure of the proposed model. Also, the variables and hypotheses of the proposed model are described in the following.

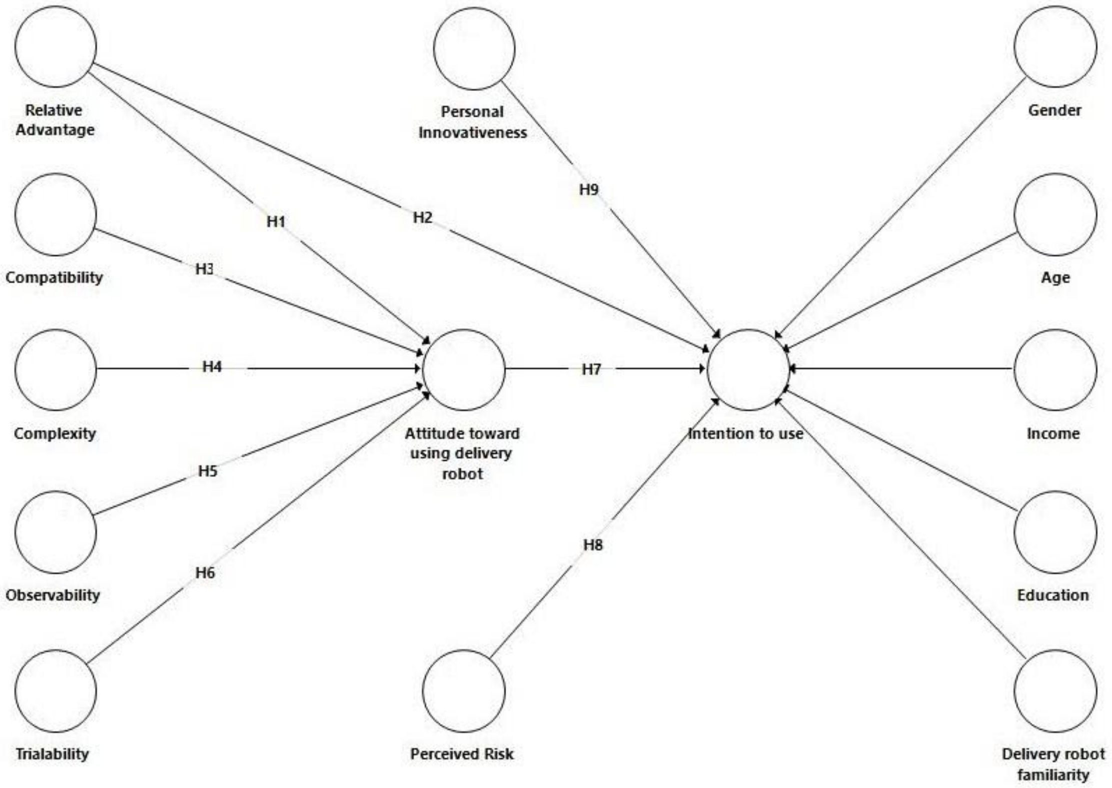

Fig. 1. Proposed model for the adoption of delivery robot

3.1. DOI and TAM constructs

3.1.1. Relative advantage

Relative advantage reflects how much more beneficial than traditional methods (i.e., vehicles or motorcycles) the use of delivery robots to deliver products is (Gkartzonikas & Gkritza, 2019). Delivery robots are more easily adopted by online shoppers when they feel that delivery robots could be better than traditional delivery methods. In other words, referring to delivery robots as a better method (e.g., in terms of the environmental impacts, economic aspects, rapidness, and convenience) positively influences the adoption of this method by online shoppers (Kapser & Abdelrahman, 2020). Relative advantage can be viewed to be similar to perceived usefulness in TAM. Hence, previous studies not only suggested the impacts of relative advantage on the attitude toward using new technologies (Tsai & Tiwasing, 2021; Yoo et al., 2018) but also investigated its direct impacts on the intention (Choudhury & Karahanna, 2008; Wang, Yuen, Wong, & Teo, 2018). As a result, Hypotheses 1 and 2 are proposed as

Hypothesis 1: The relative advantage of delivery robots over traditional methods has a positive impact on the attitude of online shoppers toward using delivery robots.

Hypothesis 2: The relative advantage of delivery robots has a positive impact on the intention of online shoppers to use delivery robots, as compared to traditional methods.

3.1.2. Compatibility

Concerning delivery robots, compatibility implies to what extent online shoppers consider delivery robots to suit their lifestyles, requirements, experience, and priorities (Yuen et al., 2020). An individual may use delivery robots rather than delivery individuals when they feel that delivery robots are compatible with their lifestyle. For example, an individual to whom the environment is important and is a priority may highly tend to employ delivery robots over traditional methods. Also, a tech-savvy is likely to try new technologies (delivery robots here) rather than traditional methods. Different studies suggested the impacts of compatibility on the attitude (Tsai & Tiwasing, 2021; Vijayasarathy, 2004; Yaprak et al., 2021). Accordingly, Hypothesis 3 is proposed as

Hypothesis 3: Compatibility with delivery robots has a positive impact on the attitude of online shoppers toward using delivery robots.

3.1.3. Complexity

Complexity indicates to what extent online shoppers feel that it is difficult and complex to learn to use delivery robots (Rogers, 1983). To employ delivery robots, online shoppers interact with a robot rather than an individual. Also, they need to have sufficient knowledge of and skill for using the required application to, for example, unlock the robot, make orders, determine delivery locations, and instantly track the robot. The tendency of an individual to use this method declines when they view this process to be complex and difficult (Kapser & Abdelrahman, 2020; Kapser et al., 2021). Complexity is similar to perceived ease of use in the TAM (with the opposite sign) and impacts the attitude toward using delivery robots. It was mentioned in different studies (Tsai & Tiwasing, 2021; Yaprak et al., 2021). Thus, Hypothesis 4 is proposed as

Hypothesis 4: The complexity of using delivery robots has a negative impact on the attitude of online shoppers toward using delivery robots.

3.1.4. Observability

Concerning delivery robots, observability indicates to what extent the advantages, use process, and learning to interact with robots can be observed by online shoppers (Wang et al., 2018). Since individuals today widely communicate with each other in social media across the world, the observation of the advantages, functions, extensions, and use process of delivery robots is publically available. Individuals can make use of the views and experiences of others, track advancements in the delivery robot technology, learn and share with others their information on how robots can be employed and interacted with, thereby contributing to the more rapid promotion of the technology (Talebian & Mishra, 2018). Thus, the higher delivery robot familiarity of individuals is expected to encourage them to employ such robots. The impacts of observability on the acceptance of new technologies have been utilized in different fields (Wang, Wong, Li, & Yuen, 2020; Wang et al., 2018; Yuen et al., 2018; Yuen et al., 2020). Hence, Hypothesis 5 is proposed as

Hypothesis 5: Observability has a positive impact on the attitude of online shoppers toward using delivery robots.

3.1.5. Trialability

Trialability refers to how possible it is for individuals to examine and try delivery robots. The users that are more interested in new and innovative technologies and services tend to have an opportunity to try new technologies and decide whether they wish to use them (Rogers, 1995). Individuals have a greater attitude toward using this method rather than traditional ones when they are allowed to try delivery robots and learn how they function before they decide on the use of delivery robots (Tan & Teo, 2000). According to Strömberg, Rexfelt, Karlsson, and Sochor (2016), trialability is an important variable that enables online shoppers to test delivery robots in a supervised environment with limited features and observe how delivery robots and their application can be used. Trialability has been proposed in the research models of many studies (Wang et al., 2018; Yuen et al., 2018). As a result, Hypothesis 6 is proposed as

Hypothesis 6: Trialability has a positive impact on the attitude of online shoppers toward using delivery robots.

3.1.6. Attitude toward using and intention to use delivery robots

According to the TAM, the intention to use delivery robots is directly influenced by the attitude toward using delivery robots (Davis, 1989). The intention to use delivery robots represents the willingness of an individual to receive products through such robots. Also, the attitude toward delivery robots indicates whether online shoppers view this method positively or negatively. An individual with a more positive attitude toward delivery robots has a higher tendency to employ this method rather than traditional methods. Many studies in different fields investigated the direct impact of the attitude toward a technology on the intention to use that technology (H.-K. Chen & Yan, 2019; Hwang, Lee, et al., 2019; Simsekoglu & Klöckner, 2019; Wang et al., 2018). Thus, Hypothesis 7 is proposed as

Hypothesis 7: The attitude toward delivery robots has a positive impact on the intention of online shoppers toward using such robots.

3.2. Added constructs

3.2.1. Perceived risk

Perceived risk can be employed as a construct added to TAM and DOI (Herzenstein, Posavac, & Brakus, 2007). According to Featherman and Pavlou (2003), perceived risk is defined as failing to achieve the desired outcome of using delivery robots as a delivery method. Regarding delivery robots, online shoppers may be concerned about the delivery process as this technology is new and its features and functions are not perfectly trusted by individuals. For example, delivering products in a damaged form or to the wrong addresses and harming objects or humans are among the concerns of online shoppers. Thus, the intention to use delivery robots is negatively impacted by perceived risk. Different studies considered the impact of perceived risk on the intention to use new technologies (H.-K. Chen & Yan, 2019; Ganjipour & Edrisi, 2022; Kapser & Abdelrahman, 2020; Kapser et al., 2021). Accordingly, Hypothesis 8 is proposed as

Hypothesis 8: Perceived risk has a negative impact on the intention of online shoppers to use delivery robots.

3.2.2. Personal innovativeness

Personal innovativeness is a key variable that influences the willingness of individuals to use delivery robots. It is commonly employed in the DOI theory (Aldás-Manzano, Lassala-Navarré, Ruiz-Mafé, & Sanz-Blas, 2009; Cheng & Huang, 2013; Yoo et al., 2018). According to Agarwal and Prasad (1998), personal innovativeness refers to the willingness of an individual to try new technologies or services. Concerning delivery robots, individuals with high personal innovativeness can deal with high uncertainty levels in the functions and features of delivery robots and be more willing to use such robots (Rogers, 1995). Thus, personal innovativeness has a positive impact on the adoption of delivery robots by online shoppers (Jackson, Mun, & Park, 2013). Many studies conducted on the adoption of new technologies or services considered the impact of personal innovativeness on the intention of individuals to use them (Y. Chen, Yu, Yang, & Wei, 2018; Cheng & Huang, 2013; Ganjipour & Edrisi, 2022). Hence, Hypothesis 9 is proposed as

Hypothesis 9: Personal innovativeness has a positive impact on the intention of online shoppers to use delivery robots.

4. Methodology

4.1. Questionnaire design

To test the hypotheses, an online questionnaire was designed to collect data from Iranian individuals that had made at least one online purchase. The questionnaire consisted of three sections. The first section introduced the questionnaire and briefly explained the advantages, applications, and functions of delivery robots system. Also, a number of images and a one and a half minute video were provided in the first section to introduce the system to the participants. In the second section, the participants were asked whether they had made online purchases. The participants that had made no online purchases were not allowed to respond to the questionnaire. The second section involved the items of nine constructs, as shown in Table 1. The seven-point Likert scale from strongly disagree (1) to strongly agree (7) was used (Likert, 1932). However, the seven-point semantic differential scale was employed for attitude and intention (e.g., unpleasant (1) / pleasant (7) for attitude, and impossible (1) / possible (7) for intention). To ensure the quality of the data, a reverse-scaled item representing "I feel delivery robot is easy to use" was included for the complexity. Responses that were scored high (or low) on this item and the item "CL1" were considered invalid. Also, in the middle of the second section, the respondents were asked irrelevant questions with evident answers to understand how much they focused on the questionnaire. The respondents that wrongly responded to the irrelevant questions were strictly treated as invalid, being excluded from the analysis. Finally, the third section of the questionnaire collected the socio-demographic information (e.g., age, gender, income, and education) of the respondents.

Since the present study was conducted in Iran, the items of the second section were translated into Persian and then back-translated into English to ensure the accuracy of the translation (Brislin, 1970). To make an accurate translation without ambiguity and to correctly convey the messages of the items (from English to Persian), three expert translators were employed. Once feedbacks were received, small modifications were applied to the wording of the items. Also, as these items have never been applied in the context of delivery robot adoption, to ensure their applicability to the present study, two pre-tests were performed. Eight relevant experts, including a professor, three Ph.D. students, and four master's students, were invited to complete the questionnaire. Feedbacks on the length of the questionnaire, the format of the scales, the number of the images and video, and the ambiguity of the items were obtained, which were reviewed and revised. In the second stage, the online questionnaire was delivered to forty-two students at the K. N. Toosi University of Technology, Iran. No feedback on the structure of the questionnaire was received, and most respondents expressed their general views on delivery robots. Thus, the unmodified version of the questionnaire was employed as the final version for the main data collection stage.

Table 1. Measurement Items with sources.

Construct	Items (7-point Likert scale)	Sources
Relative Advantage (RA)	RA1: Using delivery robot improves the parcel delivery process. RA2: Using delivery robot would enable me to receive my parcel more quick compared to home delivery (motorcycle or car). RA3: Using delivery robot would be advantageous compared to home delivery (motorcycle or car). RA4: Using delivery robot is the best way to receive my parcels.	(Meuter, Bitner, Ostrom, & Brown, 2005; Moore & Benbasat, 1991)
Compatibility (CA)	CA1: I feel Using delivery robot would be compatible with my lifestyle. CA2: I feel Using delivery robot would be compatible with my needs. CA3: I feel Using delivery robot would be compatible with my current situation.	(Meuter et al., 2005; Moore & Benbasat, 1991)

Complexity (CL)	CL1: I feel delivery robot is difficult to use. CL2: I feel delivery robot is difficult to learn how to use. CL3: I feel delivery robot is frustrating to use. CL4: I feel delivery robot is cumbersome to use. CL5: I feel delivery robot requires a lot of effort to use.	(Meuter et al., 2005; Moore & Benbasat, 1991)
Observability (OB)	OB1: I feel I can learn how to use delivery robot. OB2: I feel I can explain to others how to use delivery robot. OB3: I would have no difficulty explaining why using delivery robot is or is not beneficial. OB4: The process of using delivery robot is apparent to me.	(Meuter et al., 2005; Moore & Benbasat, 1991)
Trialability (TR)	TR1: Before deciding on whether or not to adopt the delivery robot, I would need to properly try it out. TR2: Before deciding on whether or not to adopt the delivery robot, I would need to use it on trial basis. TR3: I would be permitted to use the delivery robot on a trial basis long enough to see what it can do.	(Meuter et al., 2005; Moore & Benbasat, 1991)
Perceived Risk (PR)	PR1: The robot might malfunction and damage the package it's carrying. PR2: The robot might malfunction and damage property / injure someone. PR3: The robot might deliver my package to a different address.	(Yoo et al., 2018)
Personal Innovativeness (PI)	PI1: In general, I am among the first in my circle of friends to acquire new technology when it is appears. PI2: I can usually figure out new high-tech products and services without help from others. PI3: I keep up with the latest technological developments in my areas of interest.	(Parasuraman & Colby, 2015)
Attitude (AT)	AT1: Semantic differential - Negative/Positive AT2: Semantic differential - Unpleasant/Pleasant AT3: Semantic differential - Unfavorable/Favorable	(Collier, Sherrell, Babakus, & Horky, 2014)

Intention (IN)	IN1: Semantic differential – Impossible/Possible IN2: Semantic differential - Not probable/Very probable IN3: Semantic differential - Very unlikely/Very likely	(Collier et al., 2014)

4.2. Data collection

The final questionnaire was implemented in Google Forms. Average time of 13 minutes was required to respond to the questionnaire. The participants that responded to the questionnaire were included in a lottery for five 50 thousand tomans gift cards. The questionnaire was disseminated through social networks (i.e., Twitter, Facebook, and Instagram), online messengers (i.e., Telegram and WhatsApp), and email lists (a few universities and private companies) for two months from 10 January 2020. To improve the quality of data, a few groups of the participants were excluded. The first excluded group involved the participants that had never made online purchases. The second excluded group included the participants that wrongly responded to the irrelevant questions with evident answers. The third excluded group consisted of those that made the same response to the reverse-scaled item and "CL1". The fourth excluded group involved those that made the same responses to the entire items (i.e., zero standard deviation). Of the 328 respondents, 287 valid respondents were obtained (87.5% valid response rate), whose socio-demographic information is provided in Table 2.

Although the youth seem to over-represent the statistical population, they accounted for more than half of the Iranian online shoppers in 2018, according to the SHAPARAK statistics (Eqtesad, 2019). As the largest Iranian online shop, *Digikala.com* reported that more than 50% of its online customers were at the ages of 25-34 in the first nine months of 2019. Also, more than 66% of its customers were males, while the remaining 34% were females (Zakeri, 2019). It should be noted that more than 65% of online users in Iran are below 35 years of age, according to ChinaGoAbroad (2019). According to Armstrong and Overton (1977), nonresponse bias test was conducted. To this end, the study compared the responses (for all variables and socio-demographic characteristics) between the early and late respondents to detect significant changes. The results did not indicate significant differences.

Table 2. Descriptive statistic of sample.

Variable	Category	Frequency (n=287)	Percentage
Gender	Male	168	58.5
	Female	119	41.5
Age	<19	14	4.9
	20-29	154	53.7
	30-39	81	28.2

	40-49	18	6.3
	>50	20	7
Monthly Household Income	<2 Million Tomans	47	16.4
	2-3.9 Million Tomans	102	35.5
	4-5.9 Million Tomans	59	20.6
	6-8 Million Tomans	33	11.5
	>8 Million Tomans	46	16
Education	High school or below	20	7
	Diploma	44	15.3
	Associate degree/Some College	20	7
	Bachelor degree	136	47.4
	Master degree	49	17.1
	PhD/Doctoral or higher	18	6.3
Delivery Robot Familiarity (through the internet or media)	Familiar	139	48.4
	Unfamiliar	148	51.6

Note: 1Toman= 10 Rials (IRR)

5. Results

The structural equation model was employed to analyze the proposed model. It evaluates the relationships of latent variables with their observable indicators (known as the measurement model) and the relationships between the latent variables (known as the structural model) (Joseph F. Hair, Black, Babin, & Anderson, 2010). Also, it considers measurement errors for observed variables (Joseph F. Hair et al., 2010). The structural equation model adopts two approaches, namely the covariance-based and variance-based approaches. The partial least square (PLS) (Chin, 1998) method was selected as a variance-based approach to test the proposed hypotheses since it provides many advantages. PLS is suitable for studies with small sample sizes that do not require normal distribution (Chin, 1998). Furthermore, the PLS method is employed to analyze complicated models and fields that have not been widely investigated since it has a high statistical power (Joe F. Hair, Ringle, & Sarstedt, 2011; Joe F. Hair, Sarstedt, Ringle, & Mena, 2012). Since the proposed integrated model consists of 9 latent constructs and 31 indicators, PLS-SEM is seemingly a suitable approach. According to Anderson and Gerbing (1988), the measurement model was evaluated before the structural model by using SmartPLS v.3.2.8 (Ringle, Wende, & Becker, 2015), which is described in the following.

5.1. Measurement model

Reliability, convergent validity, and discriminant validity were evaluated to investigate the measurement model. Table 3 provides the results. As can be seen, the entire factor loadings were found to be larger than 0.5 and thus statistically significant (Joseph F. Hair et al., 2010). Cronbach's alpha should be higher than 0.6 for reliability (Taber, 2018). It was obtained to be higher than 0.6 for the entire constructs. For convergent validity, the composite reliability (CR) value should be higher than 0.7 (Chin, 1998), and the average variance extracted (AVE) needs to be greater than 0.5 (Fornell & Larcker, 1981). As can be seen in Table 3, the entire constructs obtained permissible CR and AVE values. Also, the rho_A value was obtained to be higher than 0.7 for all the constructs (Dijkstra & Henseler, 2015). For discriminant validity, the square root of AVE for each latent variable should be higher than its correlation with the other latent variables, according to Fornell and Larcker (1981). As can be seen in Table 4, the square root of AVEs (the main diagonal elements) is larger than the correlation values (below the main diagonal). Moreover, the Heterotrait-Monotrait (HTMT) ratio (above the main diagonal) is lower than its maximum value of 0.9 (Henseler, Ringle, & Sarstedt, 2015). It should be noted that the cross-loading table is provided in the Appendix.

To detect the common method bias (CMB), Harman's single factor test was employed (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). The results indicated that 30.44% of the variance was obtained by a single factor, which is lower than the maximum permissible value of 50% (Harman, 1976). Also, to determine the degree of collinearity, the variance inflation factor (VIF) values were calculated. The VIF values were obtained to be in the range of 1.020-2.055, which is lower than the maximum permissible value of 3.3 (Kock, 2015). Thus, it was revealed that the present study had no CMB or multicollinearity problems.

Table 3. Reliability indices for the measurement model.

Construct	Item	Mean (1-7)	STD	Factor Loading	T-value	α	rho_A	CR	AVE
Relative Advantage	RA1	5.547	1.137	0.824	23.990	0.862	0.871	0.907	0.709
	RA2	5.017	1.589	0.750	24.163				
	RA3	5.146	1.443	0.890	62.106				
	RA4	5.408	1.343	0.897	71.999				
Compatibility	CA1	5.174	1.559	0.882	48.615	0.855	0.867	0.912	0.775
	CA2	5.265	1.359	0.893	65.067				

	CA3	4.923	1.551	0.865	33.383				
Complexity	CL1	2.829	1.591	0.755	20.045	0.842	0.864	0.887	0.611
	CL2	2.753	1.622	0.694	12.166				
	CL3	2.237	1.280	0.851	37.668				
	CL4	2.679	1.510	0.838	33.687				
	CL5	3.139	1.831	0.759	20.665				
Observability	OB1	6.415	0.707	0.744	16.310	0.810	0.814	0.876	0.640
	OB2	6.160	0.877	0.876	41.629				
	OB3	5.718	1.250	0.780	20.679				
	OB4	5.878	1.161	0.793	24.437				
Trialability	TR1	5.909	1.254	0.990	3.570	0.884	2.169	0.894	0.742
	TR2	5.923	1.213	0.896	4.125				
	TR3	5.578	1.441	0.667	2.420				
Perceived risk	PR1	5.397	1.331	0.706	13.120	0.687	0.708	0.826	0.613
	PR2	4.118	1.777	0.835	25.912				
	PR3	3.847	1.894	0.803	22.433				
Personal innovativeness	PI1	5.052	1.524	0.652	8.318	0.680	0.728	0.815	0.598
	PI2	5.805	1.378	0.811	21.202				
	PI3	5.666	1.301	0.842	22.713				

Attitude	AT1	5.561	1.083	0.917	74.996	0.900	0.901	0.937	0.833
	AT2	5.599	1.118	0.919	74.930				
	AT3	5.418	1.180	0.902	56.994				
Intention	IN1	6.024	1.191	0.944	88.249	0.951	0.952	0.968	0.911
	IN2	5.864	1.252	0.969	178.253				
	IN3	5.655	1.264	0.951	147.252				

Note: STD=Standard Deviation, α=Cronbach's Alpha, CR=Composite Reliability, AVE=Average Variance Extracted

Table 4. AVE, correlations and Heterotrait-Monotrait (HTMT) ratio.

	AT	CA	CL	IN	OB	PI	PR	RA	TR
AT	**0.913**	0.654	0.425	0.761	0.425	0.334	0.508	0.758	0.060
CA	0.580	**0.880**	0.420	0.616	0.396	0.351	0.348	0.801	0.042
CL	-0.384	-0.372	**0.782**	0.413	0.603	0.542	0.571	0.334	0.148
IN	0.705	0.559	-0.388	**0.954**	0.462	0.420	0.492	0.608	0.046
OB	0.363	0.331	-0.492	0.405	**0.800**	0.646	0.354	0.329	0.092
PI	0.285	0.275	-0.426	0.365	0.505	**0.773**	0.386	0.223	0.193
PR	-0.408	-0.274	0.444	-0.405	-0.269	-0.282	**0.783**	0.406	0.179
RA	0.669	0.692	-0.303	0.556	0.279	0.170	-0.319	**0.842**	0.074
TR	0.078	0.030	0.096	0.067	0.006	-0.119	0.115	0.053	**0.862**

Note: The square root of AVEs is along the main diagonal (in bold). The Correlations between constructs are presented below the main diagonal and above the main diagonal the ratio HTMT. RA=relative advantage, CA=compatibility, CL=complexity, OB=observability, TR=trialability, PR=perceived risk, PI=personal innovativeness, AT=attitude, IN=intention

5.2. Structural model

In this stage, bootstrapping with 5000 subsamples was employed to test the proposed hypotheses. Table 5 shows the modeling results. To determine the predictive power of the structural model, R^2 and Q^2 values were calculated for the endogenous variables (attitude and intention). The R^2 values of 0.67, 0.33 and 0.19 are viewed to be substantial, moderate, and weak, respectively, while a Q^2 value above 0.35 represents high predictive relevance (Chin, 1998; Joe F. Hair et al., 2012). The adjusted R^2, R^2, and Q^2 values of attitude were calculated to be 0.515, 0.523, and 0.401, respectively. Also, the adjusted R^2, R^2, and Q^2 values of intention were obtained to be 0.577, 0.591, and 0.487, respectively. Thus, the model can be concluded to have suitable predictive power.

As can be seen in Table 5, the proposed hypotheses were supported, except for H6. In other words, except for trialability (β=0.047, p=0.371>0.05), the remaining variables were found to significantly impact the intention and attitude. The strongest and weakest variables impacting intention were expectedly found to be attitude (β=0.547, p=0.000<0.001) and perceived risk (β=-0.091, p=0.028<0.05), respectively. Concerning the variables impacting attitude, the strongest variable was found to be relative advantage (β=0.488, p=0.000<0.001), which was followed by compatibility. Furthermore, the impacts of four control variables, such as age, gender (male=1 and female=0), education, monthly household income, and delivery robot familiarity (through the internet or media; familiar=1 and unfamiliar=0) on intention were studied. The variables of income and delivery robot familiarity were identified to have significant, positive impacts on intention. This suggests that individuals with higher monthly income and delivery robot familiarity are more willing to use this method in the future.

Table 5. Structural Model Results.

Path	Path Coefficient	STD	T-Value	P-Values	Sig.	Results
Hypothesis						
H1: RA -> AT	0.488	0.061	8.034	0.000	***	Supported
H2: RA -> IN	0.123	0.060	2.110	0.035	*	Supported
H3: CA -> AT	0.153	0.064	2.433	0.015	*	Supported
H4: CL -> AT	-0.129	0.053	2.414	0.016	*	Supported
H5: OB -> AT	0.112	0.055	2.026	0.043	*	Supported
H6: TR -> AT	0.047	0.067	0.895	0.371	n.s.	Not supported
H7: AT -> IN	0.547	0.066	8.295	0.000	***	Supported
H8: PR -> IN	-0.091	0.042	2.193	0.028	*	Supported
H9: PI -> IN	0.146	0.072	2.012	0.044	*	Supported
Control Variables						

Age -> IN	-0.007	0.041	0.150	0.881	n.s.	Not Significant
Gender -> IN	-0.046	0.039	1.158	0.247	n.s.	Not Significant
Education -> IN	-0.045	0.038	1.202	0.229	n.s.	Not Significant
Income -> IN	0.112	0.039	2.928	0.003	**	Significant
Delivery Robot Familiarity -> IN	0.098	0.037	2.658	0.008	**	Significant

Note: *p<0.05, **p<0.01, ***p<0.001, n.s. (not significant), RA=relative advantage, CA=compatibility, CL=complexity, OB=observability, TR=trialability, PR=perceived risk, PI=personal innovativeness, AT=attitude, IN=intention

6. Discussion

The present study was conducted to understand how delivery robots could be adopted as a new delivery method by online shoppers. To this end, a model was proposed based on DOI and TAM. Also, perceived risk and personal innovativeness were added to the model. The required data were collected using an online questionnaire, testing the proposed hypothesis by the PLS-SEM approach. Let us discuss the hypothesis results.

The modeling results indicated that H6 (the impact of trialability on attitude) was statistically insignificant and rejected. This is inconsistent with Yuen et al. (2018) and Wang et al. (2018). According to Table 2, 48.4% of the respondents were familiar with delivery robots. Since delivery robots are not yet available in Iran, these respondents had obtained delivery robot familiarity through the internet. Thus, trialability might be not needed for changing and impacting the attitude of these respondents toward using delivery robots. As another possible explanation, there are few opportunities for consumers to test new technologies and services before using them in Iran. Most consumers use new technologies without any trials. Thus, they are not very familiar with the trialability of innovation before adoption.

Relative advantage was found as the most important variable affecting the attitude of the respondents. Also, it had a relatively good impact on the willingness of individuals to employ delivery robots. This is consistent with (Choi & Ji, 2015; Kapser & Abdelrahman, 2020; Wang et al., 2018; Yaprak et al., 2021; Yoo et al., 2018). It was revealed that the advantage and superior characteristics of delivery robots over traditional delivery methods impacted the adoption of such robots by online shoppers and should be taken into account by online shopping programmers. Consistent with previous studies, compatibility was expectedly found to have a significant impact on the attitude of online shoppers toward using delivery robots (Tsai & Tiwasing, 2021; Wang et al., 2018; Yuen et al., 2018). Individuals that consider delivery robots to more suit their lifestyles, requirements, and conditions have a better view of them and are more willing to use them. Complexity was found to have a relatively strong, negative impact on the attitude of the respondents (Tsai & Tiwasing, 2021; Wang et al., 2018; Yoo et al., 2018). Individuals begin to negatively view delivery robots when they feel that it is confusing and complex to receive products by interacting with delivery robots or its application rather than delivery individuals.

The results demonstrated observability to have a positive, significant impact on the attitudes of the respondents. The higher delivery robot familiarity of online shoppers through the internet and learning and observing their functions can change the attitude of online shoppers and make them more willing to use delivery robots. However, this relationship was not found to be significant in some studies (Yuen et al., 2018). As expected from previous studies, the attitude was found to be the most important factor affecting the intention (H.-K. Chen & Yan, 2019; Hwang, Kim, & Kim, 2019; Hwang, Lee, et al., 2019; Yoo et al., 2018). The attitude of an individual determines whether they adopt delivery robots. Individuals with a more positive attitude toward delivery robots have a higher tendency to use them. Personal innovativeness is another variable that has a significant impact on the intention to use delivery robots. It was mentioned in many studies (H.-K. Chen & Yan, 2019; Y. Chen et al., 2018; Hwang, Lee, et al., 2019). The individuals that are more interested in new technology and track the latest technological advancements in delivery robots are more willing to try delivery robots. Finally, perceived risk was found to have a significant, negative impact on the intention to use delivery robots. This is consistent with (Kapser & Abdelrahman, 2020; Kapser et al., 2021; Khan et al., 2019; Yoo et al., 2018). Obviously, an individual that feels more unsafe and concerned about receiving their products by delivery robots is less willing to try them.

6.1. Theoretical and practical contributions

Theoretically, this study provided a new framework based on DOI and TAM to investigate the adoption of delivery robots in Iran. Although each of TAM and DOI is alone beneficial for modeling the adoption of new technologies, the present study integrated them into a stronger model for the adoption of delivery robots. Also, two important variables, namely personal innovativeness and perceived risk, were added to the proposed model to better and more accurately investigate the factors impacting the adoption of delivery robots. These variables explain nearly 59% of the intention of online shoppers to use delivery robots.

Practically, the present study provides suitable suggestions for logistic service marketers, programmers, and providers. Since relative advantage has been known as a variable impacting the attitude toward using and intention to use new technologies, marketers should be more focused on the advantage of delivery robots over traditional delivery methods in their advertisement processes. For example, in a specific situation such as the COVID-19 pandemic where most individuals tend to make their purchases online, introducing the positive characteristics of delivery robots and their contribution to the health of individuals can draw the attention of online shoppers. Since complexity and observability have a negative and a positive impact on the attitude of individuals, respectively, marketers should train the functions of delivery robots to online shoppers through online platforms, such as social media. As a result, not only the process of using robots is introduced to online shoppers, but also its complexity reduces. Finally, programmers should not fail to consider the perceived risk. Although perceived risk has no strong impact on the intention to use robots, the entire safety and security aspects of delivery robots should be promoted so that online shoppers are encouraged to use them with lower concern.

6.2. Limitations and future studies

Several limitations of our study should be noted. First, the key limitation of this study refers to the use of an online questionnaire distributed through nonprobability sampling. This sampling procedure did not sufficiently represent the Iranian population and captured only a specific part of the online shoppers. Such procedure could cause a selection bias resulting, thus, it is suggested that future studies generalize the results by using probability sampling with a larger sample size. Second, for 51.6 percent of the participants, delivery robots were completely new. However, this is not surprising since delivery robots are in their infancy in Iran and are not publically available as a delivery alternative. These respondents were not familiar with delivery robots (even through the internet or media). They responded to the questionnaire based on the information, video, and images provided in the introduction of the questionnaire. Future studies can be more focused on participants that are more familiar with delivery robots (e.g. participants who took apart in the trials). Third, although delivery robots are not available to consumers in Iran, this study incorporated observability and trialability in the proposed model. Despite the impact of the lack of delivery robots on observability and trialability, 48.4% of the respondents had obtained familiarity with the utilization and function of delivery robots through the internet or media. In addition, the items of these two constructs were designed based on the perceptions of the respondents. This can be helpful in making policies on the establishment of a positive delivery robot attitude and the enhancement of delivery robot adoption (Yuen et al., 2020). It is suggested that future works consider the types of products, payment methods, and the working future of delivery individuals. Furthermore, other models, including the theory of planned behavior, and their integration with the other technology acceptance models can provide a suitable perspective of the factors impacting the willingness of online shoppers to use delivery robots.

6.3. Conclusions

This study investigated the factors influencing consumers' intention to use delivery robot as a new idea to compete with traditional delivery methods. The authors integrated DOI and TAM and added personal innovativeness and perceived risk to propose a new delivery robot adoption model. The PLS-SEM was employed to test the proposed hypotheses. The results indicated that relative advantage, compatibility, complexity, and observability influenced consumers' attitude toward using delivery robot; however, no significant relationship was found between trialability and attitude. Also, consumers' intention to use is affected by relative advantage, personal innovativeness, and perceived risk. The findings of this study provide significant theoretical and practical contributions to logistics service providers and marketers in the last-mile delivery context.

Appendix. Cross loadings.

	AT	CA	CL	IN	OB	PI	PR	RA	TR
AT1	**0.917**	0.539	-0.356	0.669	0.336	0.319	-0.383	0.638	0.058
AT2	**0.919**	0.516	-0.353	0.643	0.355	0.222	-0.381	0.602	0.093
AT3	**0.902**	0.532	-0.341	0.617	0.303	0.239	-0.352	0.590	0.064
CA1	0.514	**0.882**	-0.349	0.510	0.279	0.232	-0.245	0.594	0.038
CA2	0.565	**0.893**	-0.334	0.519	0.316	0.259	-0.265	0.646	0.029
CA3	0.437	**0.865**	-0.295	0.437	0.274	0.232	-0.208	0.580	0.011
CL1	-0.336	-0.359	**0.755**	-0.321	-0.375	-0.319	0.341	-0.350	0.050
CL2	-0.186	-0.200	**0.694**	-0.177	-0.429	-0.371	0.269	-0.127	0.039
CL3	-0.366	-0.343	**0.851**	-0.419	-0.414	-0.410	0.327	-0.257	0.068
CL4	-0.295	-0.309	**0.838**	-0.304	-0.420	-0.329	0.439	-0.202	0.107
CL5	-0.262	-0.188	**0.759**	-0.225	-0.304	-0.240	0.356	-0.192	0.112
IN1	0.654	0.529	-0.372	**0.944**	0.383	0.335	-0.389	0.512	0.071
IN2	0.663	0.549	-0.385	**0.969**	0.392	0.372	-0.400	0.517	0.083
IN3	0.701	0.523	-0.355	**0.951**	0.384	0.339	-0.371	0.560	0.039
OB1	0.274	0.231	-0.397	0.308	**0.744**	0.389	-0.183	0.161	0.069
OB2	0.310	0.261	-0.381	0.330	**0.876**	0.420	-0.255	0.206	0.024
OB3	0.290	0.252	-0.370	0.324	**0.780**	0.352	-0.185	0.274	-0.037
OB4	0.287	0.313	-0.429	0.333	**0.793**	0.455	-0.233	0.250	-0.034
PI1	0.113	0.164	-0.233	0.147	0.236	**0.652**	-0.147	0.111	-0.094
PI2	0.217	0.248	-0.384	0.305	0.514	**0.811**	-0.236	0.096	-0.131
PI3	0.285	0.216	-0.344	0.340	0.372	**0.842**	-0.248	0.181	-0.062
PR1	-0.237	-0.164	0.261	-0.243	-0.165	-0.163	**0.706**	-0.249	0.064
PR2	-0.388	-0.206	0.336	-0.349	-0.207	-0.194	**0.835**	-0.331	0.066
PR3	-0.316	-0.264	0.429	-0.345	-0.251	-0.295	**0.803**	-0.173	0.135
RA1	0.594	0.558	-0.267	0.500	0.248	0.134	-0.304	**0.824**	0.046
RA2	0.505	0.504	-0.127	0.356	0.144	0.084	-0.112	**0.750**	0.074
RA3	0.557	0.631	-0.315	0.486	0.240	0.159	-0.337	**0.890**	-0.015
RA4	0.590	0.629	-0.289	0.512	0.292	0.186	-0.293	**0.897**	0.077
TR1	0.092	0.033	0.087	0.079	0.020	-0.112	0.110	0.050	**0.990**
TR2	0.028	0.017	0.105	0.022	-0.031	-0.115	0.108	0.053	**0.896**
TR3	0.002	-0.001	0.156	-0.007	-0.110	-0.187	0.164	0.053	**0.667**

Note: An item's loadings on its own variable (in bold) are higher than all of its cross-loadings with other variable.

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