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The Driving and Restricting Factors of the Intention to Use the Digital Fishery Platform among Indonesia Consumer During Pandemic and New Normal: Combine UTAUT-IRT Model

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Abstract

The poor distribution system of seafood in Indonesia is a problem emerging of the high fish prices for end-users and low fish consumption. The digital fishery platform that can connect directly between fishers and end-users is expected can increase fish consumption. This study aimed to examine the influence of the Combine UTAUT-IRT factor on the digital fishery platform acceptance. Data collection was carried out through online questionnaires in Jakarta, Banten, and West Java provinces. The collected data is 360 samples, and it consists of 120 samples (33 percent) from Jakarta, 151 samples (42 percent) from Banten province, and 89 samples (25 percent) from West Java province. The research results prove that performance expectancy, effort expectancy, and social influence are determinant factors of the digital fishery platform acceptance. However, facilitating conditions did not have a significant effect on the acceptance. Then, low-value, traditional, and image barriers decrease the resistance of the digital fishery platform. Since the innovation resistance impacts digital fishery platform acceptance negatively and significantly, the low resistance increases the acceptance of the digital fishery platform. The results will be the basis for policies to build a digital fishery platform in Indonesia that connects fishers and consumers peer-to-peer through a digital platform. The originality of this study is that this is the first study to test the Combine UTAUT-IRT model in the context of a digital fishery platform.

Keywords: UTAUT, IRT, digital platform, fishery.

1. Introduction

As one of the largest archipelagic states, Indonesia has a sea area of approximately 3.25 million km2 and is rich in marine resources, especially the fishery industry. The fishery is one of the sectors that is highly relied on for national development, with an export value of US$ 5.2 billion in 2019 or an increase of 10.1% from the export value in 2018 (Pratama, 2020). Previously, the Minister of Maritime Affairs and Fisheries Ordinance No. 50 of the Republic of Indonesia stipulated that the sustainability or maximum sustainable yield (MSY) of Indonesian fish stocks should be estimated at 12,541,438 tonnes per year.

Indonesia's main problem is that even though the potential for fish resources is abundant, fish consumption in the community is still very low. Indonesian fish consumption in 2018 was only 50.69 kg per person per year, less than Malaysia (70 kg) and Singapore (80 kg). The State Program for Promoting Fish Consumption (GEMARIKAN) has increased interest in fish consumption but is not yet optimal. Apart from the fact that people like meat, another reason for low fish consumption is the low purchasing power of people and the poor distribution system of fish in the country, which is charged as a price by producers and fishermen. Very big discrepancies between prices occur by fishermen consumers are paid through long sales channels and broker games (Hidayat, 2019).

In the era of digitalization, it is possible to cut the supply or distribution chain so that the price of fish to consumers is lower. Some start-ups have launched digital platforms that allow consumers to buy fish online. However, the presence of these platforms has not maximized fish consumption because the price offered is still equal to or even more expensive than the market price. It could be because platform developers only replace brokers who buy fish from fishers and then market it through their platform. A peer-to-peer platform must connect fishers and consumers directly through digital platforms to truly cut the distribution chain. Another possibility is that the intention to take advantage of digital platforms, either from fishers, consumers, or both, is still low. Thus, the intention of fishers and consumers to use the platform and the factors that influence it need to be investigated.

Based on the above problem statement, the research questions are: (1) Which factors influence consumers' acceptance of digital platforms? (2) Which factors lead to consumer resistance to digital platforms? (3) How does resistance affect consumer acceptance of digital platforms? The investigation is carried out to ensure that the marketplace building or peer-to-peer platform can be implemented. Therefore, it is the aim of this research. Meanwhile, the urgency of this research is that finding and testing the factors that influence people's intention to shop for fish through online platforms will increase the income of fish producers (fishers) and increase fish consumption due to lower prices. Therefore, entering the new normal and continuing into the post-new normal, the online marketplace will continue to grow as part of a new culture. Thus, the research results are expected to solve the problem.

2. Literature Review

This study combines The Unified Theory of Acceptance and Use of Technology (UTAUT) model and the Innovation resistance theory (IRT). UTAUT was developed by Venkatesh et al. (2003) with its four factors, Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Condition. Meanwhile, IRT was developed by Ram and Sheth (1989) with its five, namely factors Usage Barrier, Value Barrier, Risk Barrier, Traditional Barrier, and Image Barrier.

2.1. Performance Expectancy

Performance expectancy is the extent to which individuals believe that using technology will help improve their job performance (Venkatesh et al., 2003; Venkatesh et al., 2012). According to Mahzan and Lymer (2014), the performance expectancy construct in UTAUT is related to perceived usefulness. Other previous constructs are comprised of performance expectancy are relative advantage, job fit, extrinsic motivation, and outcome expectations (Venkatesh et al., 2003). Performance expectancy explains the degree to which individuals believe that using a particular technology can improve their job performance (Mahzan & Lymer, 2014). Although Carter et al. (2011) and Purwanto and Loisa (2020) did not find the effect of performance expectancy on intention, other previous studies found that performance expectancy is the strongest factor of intention (Thompson et al., 1991; Compeau & Higgins, 1995; Venkatesh et al., 2003; Lwoga & Komba, 2015). Chang (2013), Arif et al. (2018), Ahmed et al. (2018), Alam et al. (2019), and Gunasinghe et al. (2019) also found a significant impact of performance expectancy on intention.

Based on the above previous studies, then the first hypothesis is:

H1: Performance expectancy has a positive and significant impact on consumer intention to use digital fishery platforms.

2.2. Effort Expectancy

Mahzan and Lymer (2014) also Lwoga and Komba (2015) said that the effort expectancy in UTAUT is perceived ease of use in TAM. Effort expectancy is the ease level in users' operation of a particular technology (Venkatesh et al., 2012). It is one's perception of whether it is easy or difficult to operate the system or technology (Lwoga & Komba, 2015). Thongsri et al. (2018) did not significantly impact effort expectancy on intention. Still, other previous studies such as Carter et al. (2011), Chang (2013), Arif et al. (2018), Ahmed et al. (2018), Alam et al. (2019), and Gunasinghe et al. (2019) found this construct is a significant predictor of intention to use technology.

Based on the above previous studies, then the second hypothesis is:

H2: Effort expectancy has a positive and significant impact on consumer intention to use digital fishery platforms.

2.3. Social Influence

Social influence is related to how an individual is influenced to adopt something, such as technology, because other people influence it. The other person is usually the most important in his life, and he believes that person should be his role model (Venkatesh et al., 2003). Social influence is the influence a person feels that their family and friends think they should use a particular technology (Venkatesh et al., 2012).

Thongsri et al. (2018) and Gunasinghe et al. (2019) did not significantly impact social influence on intention. Still, other previous studies such as Carter et al. (2011), Chang (2013), Arif et al. (2018), Alam et al. (2019) found this construct is a significant predictor of intention to use technology.

Based on the above previous studies, then the third hypothesis is:

H3: Social Influence has a positive and significant impact on consumer intention to use digital fishery platforms.

2.4. Facilitating Condition

Facilitating conditions relate to the level of infrastructure availability that will influence or motivate people to adopt a particular technology (Venkatesh et al., 2003; Mahzan & Lymer, 2014). Venkatesh et al. (2003) linked the facilitating conditions with usage behavior and not behavior intention. Then, Thongsri et al. (2018) and Giovanis et al. (2019) also did not examine the effect of the facilitating conditions construct on behavior intention (Venkatesh et al., 2003). But, previous studies such as Chang (2013), Ahmed et al. (2018), Gupta et al. (2019), Gunasinghe et al. (2019), and Alam et al. (2019) correlate the facilitating conditions with behavioral intention.

Gupta et al. (2019) explained that customers could be more motivated to use an application on their smartphone if it has a certain level of service and support resources. Gupta et al. (2019) study in New Delhi, India, found that the hypothesis is proven in the banking services sector. Likewise, the hypothesis is proven in Gunasinghe et al.'s (2019) study in the higher education e-Learning context in Sri Lanka. Alam et al. (2019) confirm the hypothesis is accepted in Bangladesh but rejected in China in the context of the m-Health services. Finally, Oliveira et al. (2016) mobile payment did not find a correlation between facilitating conditions with behavior intention in Portugal's mobile payment adoption context. Then, the fourth hypothesis is as the following:

Based on the above previous studies, then the fourth hypothesis is:

H4: Facilitating Conditions has a positive and significant impact on consumer intention to use digital fishery platforms.

2.5. Usage Barrier

Usage barrier is a barrier that innovation users feel because he feels that the innovation is not the same as the one he usually uses, so he refuses to adopt the technology or innovation (Sivathanu, 2019). Maybe the way he operates the new system is different from what he is used to, so he needs to relearn how to use the new system. If he feels that it will complicate his activities, he will refuse to use it. In the research results in the context of accepting digital payments, Sivathanu (2019) found that the complexity and lack of convenience of use were barriers to use, which caused consumers to refuse to use them.

Based on the above previous study, then the fifth hypothesis is:

H5: Usage Barrier has a positive and significant impact on consumer resistance to using digital fishery platforms.

2.6. Value Barrier

In general, the value attached to innovation is related to monetary value and performance. If someone judges that the innovation does not facilitate activities or improve performance, he will refuse to adopt the innovation. If the price he sacrifices for the innovation is not commensurate with the benefits he gets, he will reject the innovation. This is what is called the value barrier (Sivathanu, 2019). Sivathanu (2019) proves that the value barrier significantly affects innovation resistance.

Based on the above previous study, then the sixth hypothesis is:

H6: Value Barrier has a positive and significant impact on consumer resistance to using digital fishery platforms.

2.7. Risk Barrier

The risk of loss caused by using innovation is called a risk barrier (Ram & Sheth, 1989). It is a risk perceived by the consumers when they intend to use an innovation. Concerning online transactions, risk barriers are also related to system security problems perceived by consumers (Sivathanu, 2019). Sivathanu (2019) found that perceived risk will cause someone to refuse to use a digital payment system. This means that when a person feels that it will be risky if he uses an innovation, he will reject it.

Based on the above previous study, then the seventh hypothesis is:

H7: Risk Barrier has a positive and significant impact on consumer resistance to using digital fishery platforms.

2.8. Traditional Barrier

Traditional barriers occur when someone judges that other people in their community have not commonly used the use of certain innovations. Or even the behavior of using the innovation is contrary to the values held in their family or society (Sivathanu, 2019). For example, they are collecting offerings at church using e-money, which is unethical according to church service for some people. When people are more comfortable doing cash rather than electronically, this is a traditional barrier to adopting a digital payment system. When someone is more confident shopping in conventional markets than shopping online, it is a traditional barrier that causes them to reject online shopping innovations. Then, Sivathanu (2019) found that the traditional barrier is a significant determinant factor of innovation resistance.

Based on the above previous study, then the eighth hypothesis is:

H8: Traditional Barrier has a positive and significant impact on consumer resistance to using digital fishery platforms.

2.9. Image Barrier

Image is created from information, rumors, stereotypes related to something, such as new technology, that a person receives (Ram & Sheth, 1989). If the information received by a person regarding a particular innovation is negative, then the information can influence him to reject the innovation. It is an image barrier (Sivathanu, 2019). So then, Sivathanu (2019) found that the image barrier is a significant determinant factor of innovation resistance.

Based on the above previous study, then the ninth hypothesis is:

H9: Image Barrier has a positive and significant impact on consumer resistance to using digital fishery platforms.

2.10. Innovation Resistance and Behavior Intention

The refusal of consumers to adopt innovations because they do not want change is known as innovation resistance. The above barriers are factors that cause these innovation barriers (Sivathanu, 2019). When compared with behavior intention, then innovation resistance is the opposite. Thus, it can be hypothesized that innovation resistance will have a negative effect on behavior intention. When innovation resistance increases, behavior intention will decrease. And vice versa. So based on this logic, the tenth research hypothesis is

H10: Resistance has a negative and significant impact on consumer intentions to use digital fishery platforms.

A conceptual framework can be built based on these hypotheses, as shown in Figure 1.

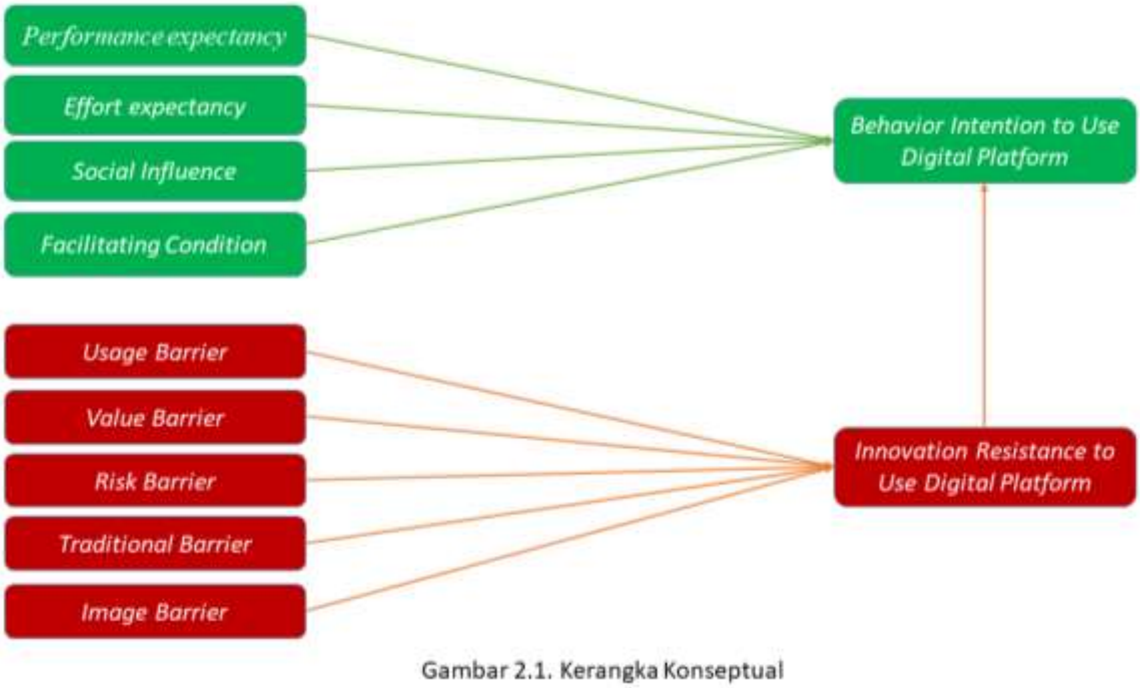

Figure 1. Conceptual Framework

2.11. Research Gaps

There is no one of the above UTAUT previous studies in the context of a digital fishery platform. And as far as literature searches on reputable journal databases can't find it either. Tarhini et al. (2016) Kuciapski (2017) Sivathanu (2019), Sobti (2019) Gupta et al. (2019), Rahi et al. (2019), Giovanis et al. (2019), Odoom & Kosiba (2020), Purwanto and Loisa (2020) study in the context of acceptance of digital payment platforms. Then, Mahzan and Lymer's (2014) study in the context of computer-assisted audit techniques and tools acceptance (CAATTs). Ahmed et al. (2018) studied in e-government service acceptance context. Then, Carter et al. (2011) studied in online tax filling context. Alam et al.'s (2019) study in the m-health service context. Then, Lwoga & Komba (2015), Arif et al. (2018), Thongsri et al. (2018), Gunasinghe et al. (2019), and Buabeng-Andoh and Baah (2020) in the e-learning context. Then, Chang (2013) and Wu and Wu (2019) study in the context of a mobile library.

As far as the search on reputable international journal databases, it is difficult to find the IRT's previous studies. And there is no found model examination in the digital fishery platform. Some previous studies examine the IRT model are in mobile banking acceptance. For example, studies by Laukkanen and Kiviniemi (2010), Chemingui and Lallouna, (2013), and Thakur and Srivastava (2013).

Then about innovation resistance, not many studies have tested this IRT. Previous studies used the IRT related to mobile banking innovation resistance (Laukkanen & Kiviniemi, 2010; Chemingui & Lallouna, 2013; Thakur & Srivastava, 2013). This study tests the IRT to measure the digital fishery platform adoption.

Compared to the results of previous studies, both on UTAUT and IRT, this study has its characteristics because the context being studied has never been investigated or researched in previous studies. This research's State of the Art can be seen in Figure 2.

Figure 2. State of the Art

The model testing in Figure 1 will be carried out on two related community entities, namely fishers and marine fish consumers. However, the test of this model will first be applied to potential marine fish consumers in the first year. This paper is the result of first-year research. Then in the second year, this model will be tested on fishermen. It will be future research. It is very important to know the intention of these two community entities for innovation in the form of a peer-to-peer digital platform before the platform itself is created. This research limits it only to discovering the results of testing the Combine UTAUT-IRT model, and further research can be carried out on applied research plans for the creation of this innovation platform.

3. Method

3.1. Population & Sample

The population is made up of consumers of saltwater fish in three states (Jakarta, Banten, and West Java). Then the samples are collected 360 samples. It consists of 120 samples (33 percent) from Jakarta, 151 samples (42 percent) from Banten, and 89 samples (25 percent) from West Java.

3.2. Sampling Technique

This study employed convenience sampling or non-probability sampling. Samples were collected from fish consumers in three Indonesian states: Jakarta, Banten, and West Java. Data collection by online sharing of questionnaires from February to April 2021.

3.3. Measurement scale

The research instrument for the variables of Performance expectancy, Effort expectancy, Social Influence, Facilitating Condition, and Behavioral intention was adapted from a questionnaire that had been developed by Venkatesh et .al. (2003). The variables “Use Barrier," “Value Barrier," “Risk Barrier," “Traditional Barrier," “Image Barrier," and “Innovation Resistance” were taken from a survey developed by Ram and Sheth (1989).

3.4. Data analysis technique

The analytical method for this study uses PLS-SEM. In PLS-SEM, the indicator's reliability is the indicator's load, and the threshold is over

0.70 (Purwanto & Purwanto, 2020). The internal consistency reliability is composite reliability, and its threshold is higher than 0.70 (Purwanto et al., 2018). The validity of convergence is the extracted mean-variance (AVE) value. The AVE value should be higher than 0.50 (Purwanto & Loisa, 2020). Finally, the significance of the hypothesis is measured by t-statistics values with a threshold above 1.96 and a p-value less than 0.05 (Purwanto et al., 2020).

4. Result

4.1. Reflective Measurement Models

Table 1 shows each indicator loading value of the behavior intention construct higher than 0.70 as the threshold of the indicator loading (Tjiu & Purwanto, 2017). Therefore, all indicator of the behavior intention construct is reliable. BI1 at 0.869, BI2 at 0.848, BI4 at 0.870, BI5 at 0.887, and BI6 at 0.775. BI3 is dropped at previous SmartPLS processing because the indicator is loading less than 0.70. The composite reliability value of the behavior intention construct is 0.929. Since the threshold of the composite reliability is higher than 0.70 (Purwanto, 2016), then the construct is reliable. The Cronbach's alpha value is 0.904. Since the threshold of Cronbach's alpha is higher than 0.70 (Karno & Purwanto, 2017), then the construct is reliable.

Table 1. Composite and Indicator Reliability of the UTAUT factors

Construct	**Items**	**Indicator Loading***	**Cronbach's Alpha***	**Composite reliability***	**Average variance Extracted (AVE)****
Behaviour Intention			0.904	0.929	0.724
	BI1	0.869			
	BI2	0.848			
	BI4	0.870			
	BI5	0.887			
	BI6	0.775			
Performance Expectancy			0.752	0.858	0.669
	PE1	0.766			
	PE2	0.833			
	PE3	0.854			
Effort Expectancy			0.757	0.860	0.672
	EE1	0.828			
	EE2	0.835			
	EE4	0.797			
Social Influence			0.784	0.874	0.699
	SI1	0.854			
	SI2	0.862			

	SI4	0.790			
Facilitating Condition			0.808	0.874	0.634
	FC1	0.740			
	FC2	0.772			
	FC3	0.847			
	FC4	0.822			

** Threshold > 0.70* *** Threshold > 0.50*

Each indicator loading value of the performance expectancy construct is higher than 0.70. Therefore all indicator of the performance expectancy construct is reliable. PE1 at 0.766, PE2 at 0.833, PE3 at 0.854. The composite reliability value of the performance expectancy construct is 0.858 > 0.70. Therefore, the construct is reliable. The Cronbach's alpha value is 0.752 > 0.70. Therefore, the construct is reliable.

Each indicator loading value of the effort expectancy construct is higher than 0.70. Therefore all indicator of the effort expectancy construct is reliable. EE1 at 0.828, EE2 at 0.835, EE4 at 0.797. EE3 is dropped at previous SmartPLS processing because the indicator loading less than 0.70. The composite reliability value of the effort expectancy construct is 0.860 > 0.70. Therefore, the construct is reliable. The Cronbach's alpha value is 0.757 > 0.70. Therefore, the construct is reliable.

Each indicator loading value of the social influences construct higher than 0.70. Therefore all indicator of the social influences construct is reliable. SI1 at 0.854, SI2 at 0.862, SI4 at 0.790. SI3 is dropped at previous SmartPLS processing because the indicator loading less than 0.70. The composite reliability value of the social influences construct 0.874 > 0.70. Therefore, the construct is reliable. The Cronbach's alpha value is 0.784 > 0.70. Therefore, the construct is reliable.

Each indicator loading value of the facilitating condition construct is higher than 0.70. Therefore all indicator of the facilitating condition construct is reliable. FC1 at 0.740, FC2 at 0.772, FC3 at 0.847, FC4 at 0.822. The composite reliability value of the facilitating condition construct is 0.874 > 0.70. Therefore, the construct is reliable. The Cronbach's alpha value is 0.808 > 0.70. Therefore, the construct is reliable.

Table 1 also shows that the AVE value of all UTAUT constructs is higher than 0.50. Therefore, all construct of the study is valid

Table 2 shows each indicator loading value of the use barrier construct higher than 0.70. Therefore all indicator of the use barrier construct is reliable. UB1 at 0.879, UB2 at 0.897, UB3 at 0.891, UB4 at 0.910. The composite reliability value of the use barrier construct is 0.941 > 0.70. Therefore, the construct is reliable. The Cronbach's alpha value is 0.917 > 0.70. Therefore, the construct is reliable.

Table 2. Composite and Indicator Reliability of the IRT Factors

Construct	**Items**	**Indicator Loading***	**Cronbach's Alpha***	**Composite reliability***	**Average variance Extracted (AVE)****
Use Barrier			0.917	0.941	0.800
	UB1	0.879			
	UB2	0.897			

	UB3	0.891			
	UB4	0.910			
Value Barrier			0.826	0.896	0.742
	VB1	0.866			
	VB2	0.848			
	VB3	0.870			
Risk Barrier			0.857	0.894	0.630
	RB1	0.732			
	RB2	0.747			
	RB3	0.765			
	RB4	0.864			
	RB5	0.851			
Traditional Barrier			0.821	0.918	0.848
	TB1	0.922			
	TB2	0.920			
Image Barrier			0.801	0.883	0.715
	IB1	0.830			
	IB2	0.843			
	IB3	0.863			
Innovation Resistance			0.820	0.893	0.736
	IR1	0.807			
	IR2	0.879			
	IR3	0.886			

** Threshold > 0.70 ** Threshold > 0.50*

Table 2 shows each indicator loading value of the value barrier constructs higher than 0.70. Therefore all indicator of the value barrier construct is reliable. VB1 at 0.866, VB2 at 0.848, VB3 at 0.870. The composite reliability value of the value barrier construct is 0.896 > 0.70. Therefore, the construct is reliable. The Cronbach's alpha value is 0.826 > 0.70. Therefore, the construct is reliable.

Each indicator loading value of the risk barrier construct is higher than 0.70. Therefore all indicator of the risk barrier construct is reliable. RB1 at 0.732, RB2 at 0.747, RB3 at 0.765, RB4 at 0.864, and RB5 at 0.851. The composite reliability value of the risk barrier construct is 0.894> 0.70. Therefore, the construct is reliable. The Cronbach's alpha value is 0.857 > 0.70. Therefore, the construct is reliable.

Each indicator loading value of the traditional barrier construct is higher than 0.70. Therefore all indicator of the traditional barrier construct is reliable. TB1 at 0.922 and TB2 at 0.920. The composite reliability value of the traditional barrier construct is 0.918> 0.70. Therefore, the construct is reliable. The Cronbach's alpha value is 0.821 > 0.70. Therefore, the construct is reliable.

Each indicator loading value of the image barrier construct is higher than 0.70. Therefore all indicator of the image barrier construct is reliable. IB1 at 0.830, IB2 at 0.843, and IB3 at 0.863. The composite reliability value of the image barrier construct is 0.883> 0.70. Therefore, the construct is reliable. The Cronbach's alpha value is 0.801 > 0.70. Therefore, the construct is reliable.

Each indicator loading value of the innovation resistance construct is higher than 0.70. Therefore all indicator of the innovation resistance construct is reliable. IR1 at 0.807, IR2 at 0.879, and IR3 at 0.863. The composite reliability value of the innovation resistance construct is 0.883> 0.70. Therefore, the construct is reliable. The Cronbach's alpha value is 0.886 > 0.70. Therefore, the construct is reliable.

Table 2 also shows that the AVE values for all IRT constructs are higher than 0.50. Therefore, all configurations of the study are valid. Table 3 also shows that the AVE of each latent structure is higher than the maximum squared correlation of the structure with other latent structures. Therefore, this study meets the validity of the identification.

Table 3. Discriminant validity (Fornell-Larcker Criterion)

	BI	**EE**	**FC**	**IB**	**IR**	**PE**	**RB**	**SI**	**TB**	**UB**	**VB**
BI	0,851										
EE	0,733	0,820									
FC	0,444	0,524	0,796								
IB	-0,231	-0,220	-0,219	0,846							
IR	-0,448	-0,346	-0,238	0,624	0,858						
PE	0,648	0,712	0,440	-0,244	-0,297	0,818					
RB	-0,156	-0,215	-0,202	0,538	0,407	-0,190	0,794				
SI	0,617	0,520	0,431	-0,075	-0,183	0,422	-0,072	0,836			
TB	-0,317	-0,273	-0,088	0,498	0,521	-0,254	0,539	-0,141	0,921		
UB	-0,012	-0,096	-0,285	0,547	0,361	-0,104	0,504	0,007	0,318	0,894	
VB	-0,323	-0,314	-0,158	0,576	0,571	-0,320	0,617	-0,094	0,578	0,540	0,862

4.2. Structural Model

The inner model evaluation starts with R^2. Adjusted R^2 values of the innovation resistance to using the digital platform are 0.672, and adjusted R^2 values of the behavior intention to use the digital platform are 0.478, the structural model can be described as moderate.

Table 4. R Square

	R Square	R Square Adjusted
Behaviour Intention to Use Digital Platform	0.676	0.672
Innovation Resistance to Use Digital Platform	0.485	0.478

Table 5 show that the H1 is accepted, which t-statistic is 4.571 > 1.96, and the p-value is 0.000 < 0.05. Likewise, H2 is accepted because t-statistic is 6.507 > 1.96, and the p-value is 0.000 < 0.05. As well as, H3 is accepted, which t-statistic is 6.190 > 1.96, and the p-value is 0.000 < 0.05. But H3 is rejected because t-statistic is 0.515 < 1.96, and the p-value is 0.607 > 0.05. Therefore, excluding the facilitating condition, others construct of the UTAUT factors determine the behavior intention to use digital fishery platform among people in Jakarta, Banten, and West Java Provinces.

Table 5. The hypothesis test

Hypotheses		**Original Sample (O)**	**T Statistics**	**P Values**	**Status**
H1	Performance Expectancy -> Behaviour Intention to Use Digital Platform	0.203	4.571	0.000	Accepted
H2	Effort Expectancy -> Behaviour Intention to Use Digital Platform	0.365	6.507	0.000	Accepted
H3	Social Influence -> Behaviour Intention to Use Digital Platform	0.313	6.190	0.000	Accepted
H4	Facilitating Condition -> Behaviour Intention to Use Digital Platform	-0.021	0.515	0.607	Rejected
H5	Use Barrier -> Innovation Resistance to Use Digital Platform	-0.051	0.884	0.377	Rejected
H6	Value Barrier -> Innovation Resistance to Use Digital Platform	0.284	4.304	0.000	Accepted
H7	Risk Barrier -> Innovation Resistance to Use Digital Platform	-0.085	1.298	0.194	Rejected
H8	Traditional Barrier -> Innovation Resistance to Use Digital Platform	0.203	3.382	0.001	Accepted
H9	Image Barrier -> Innovation Resistance to Use Digital Platform	0.433	5.984	0.000	Accepted
H10	Innovation Resistance to Use Digital Platform -> Behaviour Intention to Use Digital Platform	-0.209	5.755	0.000	Accepted

Table 5 shows that H5 is rejected because t-statistic is 0.884 < 1.96, and the p-value is 0.377 > 0.05. Likewise, H7 is rejected because t-statistic is 1.298 < 1.96, and the p-value is 0.194 > 0.05. But, H6 is accepted, which t-statistic is 4.304 > 1.96, and the p-value is 0.000 < 0.05. Likewise, H8 is accepted because t-statistic is 3.382 > 1.96, and the p-value is 0.001 < 0.05. As well as, H9 is accepted because t-statistic is 5.984 > 1.96, and the p-value is 0.000 < 0.05. Therefore, the value barrier, traditional barrier, and image barrier impact the innovation resistance to use digital fishery platform positive and significant. The result shows the low-value barrier, traditional barrier, and image barrier will decrease the innovation resistance to use digital fishery platform but increase the behavior intention to use digital platform. The H10 proves it. H10 is accepted, which t-statistic is 5.755 > 1.96, and the p-value is 0.000 < 0.05, and Original Sample is -0.209. The result shows that there is a negative and significant effect of innovation resistance on behavior intention to use digital fishery platforms. The result shows that low innovation resistance will increase behavior intention to use digital fishery platforms.

Table 6 shows that mean of the items of the behavior intention constructs is higher than 3, so it shows that people agree to use the digital fishery platform. It shows that people are interested in purchasing fresh seafood through a digital platform. People will continue to buy fresh seafood through digital platforms because they are interested in shopping on digital platforms. They love and will voluntarily buy fresh seafood directly from fishermen via the digital platform. They want to know a digital platform where I can buy fresh seafood directly from fishermen.

Table 6. Descriptive analysis of the behavior intention construct

Statement	**Mean**	**Median**	**Min**	**Max**
BI1 - I am interested in purchasing fresh seafood through a digital platform	3.828	4.000	1.000	5.000
BI2 - I will continue to buy fresh seafood through digital platforms	3.389	3.000	1.000	5.000
BI3 - I am interested in shopping on digital platforms	3.892	4.000	1.000	5.000
BI4 - I would love to buy fresh seafood directly from fishermen via the digital platform	3.822	4.000	1.000	5.000
BI5 - I will voluntarily buy fresh seafood from fishermen via the digital platform	4.133	4.000	1.000	5.000

Then, table 7 shows that mean of the items of innovation resistance construct less than 3, and it shows that people do not resist using the digital fishery platform, then it also shows that people agree to use the digital platform. It means people want to use a digital platform to buy fresh seafood and does not refuse to use digital platforms to buy fresh seafood.

Table 7. Descriptive analysis of the innovation resistance construct

Statement	Mean	Median	Min	Max
IR1 - I don't want to use a digital platform to buy fresh seafood now	2.978	3.000	1.000	5.000
IR2 - I will never use a digital platform to buy fresh seafood	2.356	2.000	1.000	5.000
IR3 - I completely refuse to use digital platforms to buy fresh seafood	2.156	2.000	1.000	5.000

The result shows that people have a high intention and low refusal to use the digital fishery platform. Then, the platform needs to be built to connect the fishers and consumers in fish buying. Since performance expectancy is a significant factor, building a platform that helps people not have to bother going to the market to buy fish is very much needed, especially in this pandemic COVID-19 situation and in the next new normal era.

5. Discussion

There has been a change in the spending patterns of the Indonesian people, especially urban consumers. They switch from shopping patterns in traditional markets to online markets. That happens because consumers have felt the benefits of making shopping activities efficient and improving their work performance. Tempo Magazine reports that spending patterns in Indonesia are changing, especially during the COVID-19 pandemic, where more people are staying at home. The development of digital payment system services, campaigns on social media, and e-commerce platforms are driving factors. Nearly sixty percent of Twitter users in Indonesia change their behavior by buying products that were previously done in person, are now done online (Widiyarti, 2020). That is the reason why this study proves that performance expectancy has a significant effect on behavior intention.

This study indicates that people are starting to realize that shopping for marine fish through a digital platform will be very beneficial for them (Baskhara, 2020). Moreover, this is very helpful during the COVID-19 pandemic. As explained by Martínez-Pérez et al. (2013), if people realize that this technology is relatively more profitable, providing efficiency in carrying out daily life activities, they will be interested in adopting the new technology. Technology that can increase productivity will be the choice of consumers (Thongsri et al., 2018).

The study results prove that effort expectancy significantly affects the intention to use the digital fishery platform. Consumers responded very well when the Ministry of Maritime Affairs and Fisheries (KKP) launched an online fish market application for Jakarta residents in collaboration with the Muara Baru Modern Fish Market. The ease of using the application is an important factor in encouraging consumers to buy fish online, especially during the Covid19 pandemic (Baskhara, 2020). *CNBC Indonesia* explained that the Covid-19 pandemic changed people's shopping styles. They have switched from conventional to online (Hasibuan, 2020). As people begin to have technological literacy, they welcome the presence of digital platforms. According to Giovanis et al. (2019), the role of the ease of the platform is urgently needed by consumers in developing countries.

This study proves the influence of social influences on the intention to use digital fishery platforms. The high role of collectivistic culture in Indonesia is important in proving this hypothesis. In highly collectivistic cultures, recommendations from relatives will significantly impact behavior among people. Many people use a digital fishery platform, which will influence others to adopt it. Information that comes from friends, family members, colleagues, and superiors and their encouragement will contribute greatly to the intention to use the digital fishery platform (Gupta et al., 2019).

This study found that facilitating conditions were not proven to affect the intention to use the digital fishery platform. Venkatesh et al. (2003) himself did not link facilitating conditions with behavior intention in the UTAUT model he developed. Venkatesh et al. (2003) associated this construct with usage behavior. However, previous studies such as Gupta et al. (2019), Alam et al. (2019), and Gunasinghe et al. (2019) linked facilitating conditions with behavioral intentions and found a significant effect of facilitating conditions on behavior intentions. If this study is not proven the hypothesis, it happens because even though Indonesia's internet infrastructure is still poor, online shopping activity is high. The survey conducted by We Are Social found that although the quality of the internet in Indonesia ranks 44th out of 46 countries surveyed, Indonesia is ranked first as a country that likes to shop through e-commerce or online shopping in 2020 (CNN Indonesia, 2021). That is why facilitating conditions are not an important factor that drives the intention to use digital platforms. Previous studies that also did not prove a significant effect of facilitating conditions on behavior intentions are by Thongsri et al. (2018) and Giovanis et al. (2019).

This study does not prove the significant effect of use barriers on innovation resistance. Use barriers are not a big problem for the people of Indonesia because Indonesia ranks first as a country whose consumers like to shop through e-commerce (CNN Indonesia, 2021). Thus, if there is a factor that encourages Indonesians to refuse to use digital platforms, it is not the use barriers factor but rather the consideration of the value of using this innovation. That is also why the effect of value barriers on innovation resistance has proven to be significant.

This study proves that value barriers significantly affect innovation resistance to use digital fishery platforms. This value barrier is related to whether the use of new technology has monetary and performance value (Sivathanu, 2019). The quality and freshness of fish sold online can be an important consideration for consumers to decide whether to buy or not. It is the value factor that consumers feel when they purchase online. Publications on *CNBC Indonesia* explained that 78.8% of consumers are still more comfortable buying conventionally for basic needs products, and 71.2% of consumers are more comfortable buying conventional fresh food ingredients. The reason is that about 66.3% of consumers admit to having problems because they cannot ensure the quality of the products purchased (Hasibuan, 2020). However, over time, online sellers guarantee the quality and freshness of the essential commodities they sell online, giving rise to trust in their consumers so that consumers do not hesitate to make purchases of basic commodities, including vegetables, meat, and fish online.

One of the Risk Barrier questionnaire questions was, “I'm worried about a sudden loss of internet connection when shopping on a digital platform.” CNN Indonesia reports that Indonesia's internet quality ranks 44th out of 46 countries. However, according to a survey, it ranks first as a country that likes to shop in e-commerce (CNN Indonesia, 2021). Another question in the Risk Barrier questionnaire is about the security of personal data of Internet users that irresponsible parties can abuse. However, according to Ismail Fahmi, an analyst at Drone Emprit and Kernels Indonesia, Indonesians tend not to understand the leakage of personal data that can be misused by irresponsible people (Ikhsan, 2021). That is why the risk barrier is not a factor affecting online shopping resistance. Instead, risk can be associated with the disadvantages users will experience when adopting new technology, including the risk of conducting online transactions (Sivathanu, 2019). So far, the online shopping experience is so secure that people don't have to worry about security risks if their digital phishing platform is equipped with a good security system.

This study proves that traditional barriers affect innovation resistance to digital fishery platforms using. Regarding the purchase of foodstuffs such as sea fish, the level of freshness and quality are the main considerations for consumers. If you buy fish directly in traditional markets, they can make a touch to ensure the quality of the fish to be purchased, but not if it is done online. That is why this traditional barrier has been proven to affect innovation resistance. However, if the online fish seller guarantees the quality of the fish, then there is no longer a traditional barrier that causes innovation resistance. In testing the IRT model, Purwanto et al. (2021) found that the traditional barriers are a significant factor in innovation resistance to using the digital fishery platform.

Image barriers are typically created by a variety of information, rumors, and stereotypes (Ram & Sheth, 1989). Image barriers related to fake news, negative news, rumors, and stereotypes affect people's reluctance to embrace new technologies (Sivathanu, 2019). Negative perceptions of the innovation image can result from negative news from the media, leading to a general rejection of innovation. The study found that image barriers influence resistance to innovation against the use of digital fishery platforms. The digital platform for this study has not yet been built, so there are no hoaxes, stereotypes, or other negative information related to this platform. Purwanto et al. (2021) also found that image barriers are a major factor in resistance to innovation when using digital phishing platforms.

Finally, this study proves that innovation resistance has a negative and significant effect on behavior intention to use the digital fishery platform. This means that when innovation resistance decreases, the intention to use will increase. Thus, to ensure the performance of the digital fishery platform to be built, developers must consider the factors of performance expectancy, effort expectancy, and social influence to increase public interest in using the platform. In addition, developers must also pay attention to value barriers, traditional barriers, and image barriers that have the potential to increase innovation resistance which will lead to decreased intention to use the digital fishery platform.

6. Conclusion

This study meets the research questions and purpose that three factors of the UTAUT influence the acceptance of digital platforms among consumers. They are only facilitating conditions that do not influence acceptance. Then the IRT factors use barrier and risk barrier do not influence the resistance to digital platforms, but value, traditional, and image barriers do. Then, the study finds that the people have low resistance and high acceptance of the digital fishery platform, and the resistance has a negative and significant effect on acceptance. Therefore, when the resistance decrease, then the acceptance increase.

Based on the above findings, it is very important to build a digital fishery platform to connect the fishers with their consumers directly through a peer-to-peer platform. It is very promising, especially in the COVID-19 pandemic when physical and social distancing is characteristic of this situation. This situation will continue into a new normal era. So, it is an opportunity for a start-up to build the platform as soon as possible.

This study is part of a multi-year study. Investigate the consumers' intention in the first year, and investigate the fishers' intention in the second-year study. Then, the limitation of the study is it is the only investigation among consumers, and an investigation among fishers has not been conducted yet. Therefore, the recommendation for the future is to implement a second-year study and investigate the fishers' intentions. With the use of this C-UTAUT-IRT model, other researchers also can do investigate consumers' and fishers' intentions simultaneously at the same time in other regions or countries.

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