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QR code and mobile payment: The disruptive forces in retail

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ABSTRACT

The emergence of mobile payment (m-payment) resulted in the disruption of many sectors in the business sphere, particularly the retail industry. However, the acceptance of m-payment still has substantial room for improvement. Therefore, this study purports to ascertain the critical antecedents that impact the m-payment adoption intention, in particular the type of m-payment that utilizes the Quick Response (QR) code technology, through an extended Mobile Technology Acceptance Model. On top of offering several theoretical implications, numerous practical implications are also provided for stakeholders in the retail sector.

1. Introduction

In recent years, the general public is no longer constrained to paying for products and services with cash or credit/debit cards as the number of payment methods available has increased (de Luna et al., 2019). One of which is mobile payment (m-payment), a versatile mobile service that enables consumers to procure products and services via the utilization of a smartphone (Chawla and Joshi, 2019). In Malaysia, the government has realized the benefits of m-payment and has been putting in efforts to accelerate the promotion of its adoption (Lee and Khaw, 2018), such as providing eligible Malaysians who use m-payment a one-off RM30 incentive in 2020 (Zahid, 2019). With regards to this, only three of the leading m-payment service providers were selected to disburse the incentive to their users, namely, Touch ‘n Go eWallet, Boost, and GrabPay (Khazanah Nasional Berhad, 2019). However, it is shocking that m-payment is not frequently used in Malaysia. M-payment only made up about 10% of total payments in Malaysia (Yuen, 2019). Additionally, cash and cards are still presently the top payment methods used despite the efforts to shift Malaysia into a cashless society (Nielsen, 2019). All these points to the fact that there is a need to better understand the drivers of Quick Response (QR) code m-payment adoption as the country looks to shift to a cashless society.

In light of this, the Mobile Technology Acceptance Model (MTAM) was utilized as the base model in view that the subject matter of this study is a mobile-related service. Furthermore, this study extends the model as the base of MTAM only has two constructs. As such, the research objectives are to look into the main antecedents that impact the adoption of m-payment through a developing nation’s viewpoint as well as to test the robustness of MTAM with additional variables from other dimensions.

Practically, m-payment has the potential to be a significant disruptor in many sectors. However, due to the low utilization of m-payment by users in Malaysia, there is a presence of untapped potential in terms of its future applications (Yuen, 2019). Therefore, this setting provides businesses with numerous possibilities to enhance their operational processes. Overall, this study provides insights and findings that are of significant value to numerous stakeholders such as the government and business operators. Besides, past studies that have looked into m-payment were mainly approached from a general perspective. Given that there are a number of different m-payment which uses near field communication (NFC) technology, QR code, and others (de Luna et al., 2019), the focus of this research is particularly on the QR code m-payment as the leading m-payment service providers in Malaysia are providing their service based on this technology (Khazanah Nasional Berhad, 2019). Additionally, the antecedents impacting the m-payment adoption intention are investigated through a uniquely extended MTAM that includes other relevant variables for more comprehensive findings. Overall, this uniquely extended model and its findings advance the current development of mobile technology acceptance literature.

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2. Literature review

2.1. Mobile Technology Acceptance Model (MTAM)

The MTAM was established by Ooi and Tan (2016) in view of the original Technology Acceptance Model’s (TAM) inherent weaknesses. One of the primary limitations of TAM is its original definition. In its truest form, the definitions of variables are confined within an organizational context. This is an issue as technology adoption beyond the workplace varies on numerous aspects such as the types and intricacies of tasks (Brown et al., 2006). Additionally, users respond differently to an electronic and mobile setting. For example, mobile users’ perceived ease of use would be different from those using desktop computers when it comes to battery life and screen size (Tan et al., 2014). As such, MTAM was developed to specifically tailor to the mobile environment for information technology research. The researchers comprehensively looked into and provided extensive elaborations on prominent information technology models utilized to comprehend the adoption of innovative technology and their limitations in mobile research. Based on that, they came up with this model that comprises two variables, namely mobile usefulness (MU) and mobile ease of use (MEOU).

Besides, TAM alone is not comprehensive in accounting for the changes in innovative technology adoption (Gu et al., 2009). TAM was found to hardly be able to make up for 40% of the changes in usage intention and behaviour of new technology adoption (Legris et al., 2003). With only two determinants, TAM lacks other variables that would be considered vital in influencing the adoption of innovative technology (Luarn and Lin, 2005). Phan and Daim (2011), as well as Benbasat and Barki (2007), suggested that overcoming this drawback would require more variables to be added to reach a more detailed comprehension of the antecedents that affect the innovative technology adoption, particularly for mobile services. As such, factors beyond the technological dimensions should be included (Kim et al., 2010; Chen, 2008). Additionally, Ooi and Tan (2016) originally proposed the MTAM as an extended model. They studied the adoption of smartphone credit card using MU and MEOU (i.e., the MTAM variables) with other additional variables.

As such, MTAM is the most suitable model as the context of this study is very similar to the original setting which it was first developed for. As the determination of successful adoption is multi-dimensional (Tan et al., 2014; Leong et al., 2013), an extension of the MTAM was done in order to shed more light on QR code m-payment by incorporating other critical variables namely perceived transaction convenience (PTC), perceived transaction speed (PTS), optimism (OP), and personal innovativeness (PI). The proposed framework is shown in Fig. 1.

3. Hypotheses development

MU in this study is regarded as the degree to which the use of QR code m-payment enhances the individuals’ performance in making transactions (Kaatz, 2020; Ooi and Tan, 2016). Specifically, mobile technology or service represents the QR code m-payment in this study. As users will evaluate the perks of utilizing QR code m-payment with other payment methods before adopting it (Shankar and Datta, 2018), its usefulness would be significant in determining its adoption. The behavioral intention (BI) for QR code m-payment adoption was found to be significantly affected by usefulness (de Luna et al., 2019). Moreover, the significant effect of usefulness on the BI to adopt m-payment is similar in the Southeast Asian context (Nguyen et al., 2016). Specifically, Ooi and Tan (2016) found that MU has a significant impact on the BI of m-payment in Malaysia. Thus, the hypothesis below was developed:

**H1.** MU has a positive relationship with BI to adopt QR code m-payment.

MEOU is defined in this study as the degree to which the use of QR code m-payment is free from effort (Ooi and Tan, 2016). Contextually, in this study, mobile technology or service represents the QR code m-payment. In order for users to incline to adopt QR code m-payment, it has to be easy with regards to the efforts required to learn and use. The significance of MEOU on the BI to adopt m-payment is prevalent. Studies by Arvidsson (2014), Nyaboga et al. (2015), as well as Shankar and Datta (2018) which were carried out in Sweden, Kenya, and India respectively discovered that ease of use is a vital antecedent in affecting the BI to adopt m-payment. Specifically, in Malaysia, Tan et al. (2014) found that MEOU has a significant positive relationship with BI to adopt m-payment. Thus, the hypothesis below was developed:

**H2.** MEOU has a positive relationship with BI to adopt QR code m-payment.

In this study, PTC refers to the extent to which the individuals perceive the QR code m-payment increases convenience in the payment process (Chen, 2008; Boden et al., 2020). A single m-payment service has the ability to replace multiple payment alternatives such as cash and credit/debit cards (Rampton, 2017). Thus, users can store and use multiple card accounts into an m-payment service and enjoy the convenience of not having to bring cash as well as multiple plastic cards around. PTC has been discovered to significantly influence the usefulness of m-payment by a number of past studies (De Kerviler et al., 2016; Chan and Nath, 2008). In other words, part of the usefulness that affects the m-payment adoption intention is in the form of convenience. More specifically, users are only required to scan the QR code and authenticate the transaction with their m-payment device. Thus, the hypothesis below was developed:

**H3.** PTC has a positive relationship with MU.

Adapted from Chen (2008), PTS in this study is defined as the extent to which the individuals perceive the QR code m-payment improves the

![](https://example.com/fig1.png)

Fig. 1. Proposed theoretical model.
speed of transaction in payment process. As of today, the speed of the internet and data transaction in Malaysia has increased substantially in recent years (Yunus and Jalil, 2019). This will facilitate users to carry out the payment process quicker with QR code m-payment which will ultimately contribute to its ease of use. Specifically, the significant influence of PTS on the ease of use of m-payment in Malaysia was found by Teo et al. (2015). In other words, part of the ease of use that impacts the m-payment adoption intention is in terms of speed. QR code m-payment is characterized by its quick response technology which ultimately results in the fast completion of transactions. Therefore, the hypothesis below was developed:

**H4.** PTS has a positive relationship with MEOU.

OP refers the positive outlook towards technology whereby it provides increased efficiency, flexibility, and control in people’s lives (Parasuraman and Colby, 2015). Walczuch et al. (2007) added that those who are optimistic would be less likely to emphasize on the negative aspects and thus, would have a greater propensity to adopt innovative technology. However, numerous past studies have only examined the impact of OP towards usefulness and ease of use. Despite the varying results, the general finding was that OP have a positive relationship with usefulness and ease in mobile-related settings (Oh et al., 2014; Shin and Lee, 2014; Kumar and Makherjee, 2013). Furthermore, Humbani and Wiese (2018) looked into the direct influence of OP on m-payment adoption and found them to be positively related. Thus, the hypothesis below was developed:

**H5.** OP has a positive relationship with BI to adopt QR code m-payment.

PI is defined as the level of which an individual is willing to explore new m-payment methods (Kim et al., 2010). In a number of studies, PI was identified as a significant factor in new product adoption although not incorporated into the more popular models of technology acceptance (Cowart et al., 2008). The findings of other recent studies supported the significant positive effect that PI has on the m-payment adoption intention in different geographical contexts (Zhang et al., 2018; Makki et al., 2016; Oliveira et al., 2016). One study, in particular, examined the antecedent influencing non-users’ m-payment adoption intention in the United Kingdom and it was also found that PI is a significant determinant (Slade et al., 2015). Thus, the hypothesis below was developed:

**H6.** PI has a positive relationship with BI to adopt QR code m-payment.

Fig. 1 shows the proposed theoretical model based on the aforementioned hypotheses.

### 4. Research methodology

The target respondents were smartphone users in Klang Valley. This is because the subject matter of this study heavily involves the use of a smartphone and Klang Valley has approximately one-quarter of Malaysian total population (Department of Statistics Malaysia, 2018). Moreover, Selangor and Kuala Lumpur which are encompassed under the Klang Valley region have the first and third highest number of smartphone users in Malaysia respectively (Statista, 2019). Particularly, the sampling locations were selected from the list of five large shopping malls in Klang Valley (Chin, 2018). The reason being was that high traffic of consumers with different demographics are present in shopping malls (Wong et al., 2015; Tan and Ooi, 2018). Additionally, the timing of the data collection varied in order to prevent sample bias (Hew et al., 2017).

As the sample requires a level of filtering in order to ensure the selection of participants who have the relevant knowledge or experience with the current study’s subject matter, purposive sampling was utilized (Etikan et al., 2016). Overall, purposive sampling allows the data collected to be more reflective of the situation at hand. Hence, prospective respondents were first enquired if they own a smartphone before being solicited for their participation in the survey. The questionnaires were only given to those who agreed to participate and were collected as soon as the participants completed all the sections.

The data collection tool was survey questionnaire which was developed with reference to past studies. All the measurement items were gauged using a seven-point Likert scale that ranges from (1) strongly disagree to (7) strongly agree. The questionnaire items and respective references are listed in Table 1.

Besides, the “10 times rule” proposed by Hair et al. (2017) was utilized to set the minimum sample size. Altogether, there are four structural paths pointed to the endogenous variable with the most number of incoming structural paths (i.e., BI). Hence, 40 responses were calculated

| Constructs | Measurement Items | Sources |
|------------|-------------------|---------|
| **Mobile Usefulness (MU)** | MU1: Using QR code mobile payment improves my productivity in purchasing. MU2: Using QR code mobile payment enhances my effectiveness in my daily work. | Ooi and Tan (2016) |
| **Mobile Ease of Use (MEOU)** | MEOU1: Learning to use QR code mobile payment is easy for me. MEOU2: Using QR code mobile payment does not require a lot of mental effort. MEOU3: Interaction with QR code mobile payment is clear and understandable. MEOU4: It would be easy for me to become skillful at using QR code mobile payment services. | Ooi and Tan (2016) |
| **Perceived Transaction Convenience (PTC)** | PTC1: QR code mobile payment is simple and convenient. PTC2: QR code mobile payment is always accessible. PTC3: I am able to complete my purchases without difficulty. | Teo et al. (2015) |
| **Perceived Transaction Speed (PTS)** | PTS1: I believe that using QR code mobile payment will improve the speed of transaction. PTS2: Using QR code mobile payment helps me to reduce time spent in shopping. PTS3: Compared to traditional payment methods, I believe that transactions will be fast if I use QR code mobile payment. | Teo et al. (2015) |
| **Optimism (OP)** | OP1: Technology gives me more control over my daily life. OP2: Products and services that use the newest technologies are much more convenient to use. OP3: I like the idea of doing business via technology because I am not limited to regular means. | Lu et al. (2011) |
| **Personal Innovativeness (PI)** | PI1: I like to experiment with new technology. PI2: I would look for ways to try-out with new technology. PI3: Among my peers, I am usually the first to try out new technology. | Slade et al. (2015) |
| **Behavioral Intention (BI)** | BI1: I intend to increase the use of QR code mobile payment in the future. BI2: I intend to use QR code mobile payment when the opportunities arise. BI3: I would like to use QR code mobile payment for purchasing instead of traditional payment methods (e.g. Cash) BI4: I will strongly recommend to others to use QR code mobile payment. | Tan et al. (2014) |
as the minimum sample size to run the partial least squares-structural equation modeling (PLS-SEM) analysis. Moreover, the G*Power version 3.1 with a statistical power of 0.8, margin error of 0.05, effect size of 0.15, and six predictors was also used to determine the minimum sample size. The result recommends a minimum sample size of 98. The minimum sample size is referring to the lower bound of sample size required to confirm or reject the existence of a minimum effect.

5. Data analysis

5.1. Respondents’ profile

Based on Table 2, the gender mix between males and females was 45.9% and 54.1% respectively. The respondents were predominantly young as those below 20 years old and 21–25 years old made up a large majority of the respondents. As such, it is reflective that many of the respondents were students who have yet to or are currently pursuing tertiary education. With regard to this, it is also in line that almost half of them earned a monthly income of less than RM1000. Lastly, when it comes to using QR code mobile payment in the past 12 months, more than half indicated 1–10 times whereas nearly one-fifth of them indicated 11–20 times.

5.2. Statistical analysis

The PLS-SEM analysis was engaged via SmartPLS version 3.2.8 to analyze the measurement and structural models. As proposed by Tan et al. (2018), PLS-SEM is suitable due to its higher prediction accuracy of complex research models. Additionally, PLS-SEM can accommodate the violation of the data normality distribution. Using Web Power online tool, Mardia’s coefficient of multivariate skewness was (β = 9.08, p < 0.001) and Mardia’s multivariate kurtosis was (β = 87.54, p < 0.001), thus giving support that the data was not normally distributed. Hence, the suitability of utilizing PLS-SEM is established.

5.2.1. Common method bias (CMB)

Because the collection of multiple variable data was from the same subject in the questionnaire survey, CMB may be present. To check on the magnitude of such bias, a common method factor analysis was engaged (Liang et al., 2007). All R² were statistically significant at p < 0.001 with an average of 0.86 as shown in Table 3. Additionally, 22 of 24 R² are not significant with small and negative values. Thus, CMB has been determined to not be a significant issue.

5.3. Assessing the outer measurement model

Composite reliability (CR) and Cronbach’s Alpha were utilized to test

| Construct | Indicator | Substantive factor loading (Ra) | R² | Method factor loading (Rb) | Rb² |
|-----------|----------|-------------------------------|----|---------------------------|-----|
| BI        | B1 - B1  | 0.84***                       | 0.71 | -0.01                  | 0.00 |
|           | B2 - B1  | 0.95**                       | 0.90 | -0.12                  | 0.01 |
|           | B3 - B1  | 0.83**                       | 0.69 | 0.06                  | 0.02 |
|           | B4 - B1  | 0.75**                       | 0.56 | 0.13                  | 0.02 |
| MEOU      | MEOU1    | 0.84**                       | 0.71 | 0.03                  | 0.00 |
|           | MEOU2    | 0.95**                       | 0.90 | -0.14                  | 0.02 |
|           | MEOU3    | 0.84**                       | 0.71 | 0.05                  | 0.00 |
|           | MEOU4    | 0.82**                       | 0.68 | 0.06                  | 0.00 |
| MU        | MU1 - MU1| 0.91**                       | 0.82 | -0.02                  | 0.00 |
|           | MU2 - MU1| 0.91**                       | 0.82 | -0.01                  | 0.00 |
|           | MU3 - MU1| 0.82**                       | 0.67 | 0.08                  | 0.01 |
|           | MU4 - MU1| 0.94**                       | 0.88 | -0.05                  | 0.00 |
| OP        | OP1 - OP1| 0.92**                       | 0.85 | -0.07                  | 0.01 |
|           | OP2 - OP1| 0.87**                       | 0.75 | 0.01                  | 0.00 |
|           | OP3 - OP1| 0.79**                       | 0.63 | 0.02                  | 0.00 |
| PI        | PI1 - PI1| 0.85**                       | 0.73 | 0.05                  | 0.00 |
|           | PI2 - PI1| 0.92**                       | 0.85 | 0.06                  | 0.00 |
|           | PI3 - PI1| 0.79**                       | 0.62 | -0.06                 | 0.00 |
| PTC       | PTC1     | 0.71**                       | 0.50 | 0.21                  | 0.04 |
|           | PTC2     | 0.92**                       | 0.84 | -0.10                 | 0.01 |
|           | PTC3     | 0.96**                       | 0.95 | -0.11                 | 0.01 |
| PTS       | PTS1     | 0.85**                       | 0.73 | 0.03                  | 0.00 |
|           | PTS2     | 0.91**                       | 0.83 | -0.14                 | 0.02 |
|           | PTS3     | 0.80**                       | 0.64 | 0.09                  | 0.01 |

Average 0.86 0.75 0.00 0.01

Notes: a. BI = Behavioral Intention; MU = Mobile Usefulness; MEOU = Mobile Ease of Use; PTC = Perceived Transaction Convenience; PTS = Perceived Transaction Speed; OP = Optimism; PI = Personal Innovativeness.
b. **p < 0.001, *p < 0.01, NS p > 0.05.

Table 2

| Demographic characteristic | Frequency | Percentage (%) |
|---------------------------|-----------|----------------|
| Gender                    |           |                |
| Male                      | 153       | 45.9           |
| Female                    | 180       | 54.1           |
| Age                       |           |                |
| 20 years old and below    | 103       | 30.9           |
| 21–25 years old           | 149       | 44.7           |
| 26–30 years old           | 45        | 13.5           |
| 31–35 years old           | 19        | 5.7            |
| 36–40 years old           | 12        | 3.6            |
| 40 years old and above    | 5         | 1.5            |
| Current education level   |           |                |
| No college degree         | 75        | 22.5           |
| Diploma/Advanced diploma  | 82        | 24.6           |
| Bachelor degree/Prof degree | 151     | 45.3           |
| Master/PhD degree         | 25        | 7.5            |
| Occupation                |           |                |
| Student                   | 171       | 51.4           |
| Working Professional      | 98        | 29.4           |
| Self-employed             | 32        | 9.6            |
| Others                    | 32        | 9.6            |
| Monthly income            |           |                |
| Below or equal to RM1000  | 165       | 49.5           |
| RM1001-RM2000             | 46        | 13.8           |
| RM2001-RM3000             | 65        | 19.5           |
| RM3001-RM4000             | 25        | 7.5            |
| RM4001-RM5000             | 13        | 3.9            |
| RM5001 and above          | 19        | 5.7            |
| Frequency of using QR code mobile payment in the past 12 months | | |
| 1–10 times                | 176       | 52.9           |
| 11–20 times               | 66        | 19.8           |
| 21–30 times               | 22        | 6.6            |
| 31–40 times               | 25        | 7.5            |
| More than 40 times        | 44        | 13.2           |
reliability. With reference to Table 4, all the values of CR and Cronbach’s Alpha are 0.81 and above. This implies that all the measures of the constructs adopted in this research have very good reliability (Sekaran and Bougie, 2016). Furthermore, convergent validity is also achieved as all the constructs’ Average Variance Extracted (AVE) are above 0.50 whereas every measurement item’s outer loading value is above 0.70 (Hair et al., 2017). Besides, Hetero-Trait-Mono-Trait (HTMT) inference was utilized to evaluate discriminant validity. The confidence interval results in Table 5 shows that all values are below one, which clearly supports that all the constructs are different from one another by empirical standards (Hair et al., 2017).

5.4. Inspecting the inner structural model

With a p-value of 0.05 or lower set as the significance level, the inner structural model was analyzed. Table 6 and Fig. 2 show that besides H2 and H6, all other hypotheses were supported. MU (β = 0.294, p < 0.001) and OP (β = 0.255, p < 0.001) are significantly associated to the BI to adopt QR code mobile payment. Furthermore, PTS (β = 0.689, p < 0.001) and PI (β = 0.602, p < 0.001) have significant association with MU and MEOU respectively. Conversely, two constructs which are MEOU (β = 0.111, p > 0.05) and PI (β = 0.074, p > 0.05) were unsuccessful in envisaging the BI to adopt QR code mobile payment.

Overall, 39.2% of the changes in BI to adopt QR code mobile payment were explained by all the variables utilized. Furthermore, PTC and PTS account for 47.5% of the changes in MU and 36.2% of the changes in MEOU respectively.

5.5. Predictive relevance and effect size

With the recommendation by Hair et al. (2017) as the best approach in assessing the predictive relevance, the cross-validated redundancy was used to calculate Stone-Geisser’s $Q^2$. Based on Table 7, the model exhibits predictive relevance because the $Q^2$ values are more than zero.

Table 4: Loadings, composite reliability, Cronbach’s alpha and average variance extracted.

| Constructs | Items | Loadings | Composite Reliability (CR) | Cronbach’s Alpha | Average Variance Extracted (AVE) |
|------------|-------|----------|-----------------------------|------------------|----------------------------------|
| BI         | B1    | 0.822    | 0.907                       | 0.864            | 0.709                            |
|            | B2    | 0.839    |                             |                  |                                  |
|            | B3    | 0.840    |                             |                  |                                  |
|            | B4    | 0.866    |                             |                  |                                  |
| MU         | MU1   | 0.887    | 0.940                       | 0.914            | 0.795                            |
|            | MU2   | 0.903    |                             |                  |                                  |
|            | MU3   | 0.890    |                             |                  |                                  |
|            | MU4   | 0.886    |                             |                  |                                  |
| MEOU       | MEOU1 | 0.868    | 0.920                       | 0.884            | 0.741                            |
|            | MEOU2 | 0.820    |                             |                  |                                  |
|            | MEOU3 | 0.882    |                             |                  |                                  |
|            | MEOU4 | 0.872    |                             |                  |                                  |
| PTC        | PTC1  | 0.893    | 0.898                       | 0.831            | 0.747                            |
|            | PTC2  | 0.825    |                             |                  |                                  |
|            | PTC3  | 0.872    |                             |                  |                                  |
| PTS        | PTS1  | 0.890    | 0.887                       | 0.810            | 0.724                            |
|            | PTS2  | 0.788    |                             |                  |                                  |
|            | PTS3  | 0.873    |                             |                  |                                  |
| OP         | OP1   | 0.862    | 0.895                       | 0.825            | 0.740                            |
|            | OP2   | 0.859    |                             |                  |                                  |
|            | OP3   | 0.860    |                             |                  |                                  |
| PI         | PI1   | 0.873    | 0.891                       | 0.813            | 0.732                            |
|            | PI2   | 0.917    |                             |                  |                                  |
|            | PI3   | 0.770    |                             |                  |                                  |

Notes:
BI = Behavioral Intention; MU = Mobile Usefulness; MEOU = Mobile Ease of Use; PTC = Perceived Transaction Convenience; PTS = Perceived Transaction Speed; OP = Optimism; PI = Personal Innovativeness.

Table 5: Hetero-Trait-Mono-Trait (HTMT inference).

| Paths | Original Sample (O) | Sample Mean (M) | 2.50% | 97.50% |
|-------|---------------------|-----------------|-------|--------|
| MEOU -> BI | 0.581 | 0.582 | 0.462 | 0.691 |
| MU -> BI | 0.630 | 0.630 | 0.523 | 0.725 |
| MU -> MEOU | 0.817 | 0.816 | 0.741 | 0.882 |
| OP -> BI | 0.634 | 0.634 | 0.516 | 0.737 |
| OP -> MEOU | 0.702 | 0.703 | 0.610 | 0.789 |
| OP -> MU | 0.701 | 0.701 | 0.613 | 0.782 |
| PI -> BI | 0.478 | 0.477 | 0.345 | 0.599 |
| PI -> MEOU | 0.543 | 0.545 | 0.406 | 0.679 |
| PI -> MU | 0.492 | 0.493 | 0.355 | 0.622 |
| PI -> OP | 0.733 | 0.733 | 0.625 | 0.831 |
| PTS -> BI | 0.694 | 0.694 | 0.593 | 0.784 |
| PTS -> MEOU | 0.734 | 0.733 | 0.626 | 0.824 |
| PTS -> MU | 0.784 | 0.782 | 0.699 | 0.853 |
| PTS -> OP | 0.736 | 0.736 | 0.645 | 0.816 |
| PTS -> PI | 0.557 | 0.559 | 0.416 | 0.698 |
| PTS -> BI | 0.785 | 0.785 | 0.701 | 0.860 |
| PTS -> MEOU | 0.704 | 0.704 | 0.604 | 0.794 |
| PTS -> MU | 0.725 | 0.724 | 0.631 | 0.806 |
| PTS -> OP | 0.652 | 0.652 | 0.539 | 0.759 |
| PTS -> PI | 0.540 | 0.541 | 0.399 | 0.674 |
| PTS -> MEOU | 0.864 | 0.863 | 0.791 | 0.927 |

Notes:
MEOU = Mobile Ease of Use; MU = Mobile Usefulness; MEOU = Mobile Ease of Use; PTS = Perceived Transaction Convenience; PTS = Perceived Transaction Speed; OP = Optimism; PI = Personal Innovativeness.

For the effect size, $f^2$ was assessed to establish the intensity of relationships among variables (Cohen, 2013). The intensity of relationships is categorized under small, medium, or large if the $f^2$ value ranges between 0.020 and 0.149, 0.150 to 0.349, or 0.350 and above respectively (Gefen and Straub, 2005). Moreover, there is no effect if the $f^2$ has a value of less than 0.020 (Kemény et al., 2016). Table 8 shows that MEOU and PI have no effect whereas MU and OP have small effects on BI. Furthermore, PTC and PTS have large effects on MU and MEOU respectively. It is also important to address on the model’s out-of-sample predictive power since the $R^2$ only concentrated on the sample explanatory power (Loh et al., 2019). Thus, this study further applied PLSpredict by concentrating on the endogenous construct BI (Shmueli et al., 2016). First, the results in Table 9 show that all indicators for BI have positive $Q^2$ predict value. Second, the model lacks predictive power as all of the root mean squared error values have greater prediction error compared to the linear model benchmark.

6. Post hoc analysis

6.1. Robustness check: unobserved heterogeneity

Unobserved heterogeneity which is the “differences between two or more groups of data do not emerge a priori from a specific observable characteristic or combinations of several characteristics” (Hair et al., 2018, p. 138) was checked using FIMIX-PLS. Failing to check for unobserved heterogeneity in the proposed model will result in both Type 1 and Type 2 errors (Becker et al., 2013). According to Loh et al. (2019), the best solution is judged according to the smallest value for all the defined criteria except LnL which is based on the highest number. The result in Table 10 indicated that 1-segment, 2-segment and 3-segment models have 1-segment solution each. 4-Segment model possess the highest amount of optional solutions with 5-segment model. As Table 11 also shows that 4-segment model represents 10.7% of the data, this particular segment has been chosen. Heterogeneity is not a problem in this study as the weighted average $R^2$ values of the 4-segment model are greater compared to the full dataset as shown in Table 12 (Hair et al., 2018).
6.2. Importance performance map analysis (IPMA)

The identification of possible areas for the improvement of constructs was done using IPMA. Specifically, the goal of IPMA is to determine the antecedents that have high importance for a specific construct but with low performance (Ringle and Sarstedt, 2016). Table 13 and Fig. 3 present the IPMA results for the criterion BI. Out of the six predictors, MU has the highest importance (0.281), followed by OP (0.258), PTC (0.206), PI (0.073), PTS (0.071), and MEOU (0.117).
PTC shows the highest performance at (74.865), followed by MU (72.558), PTS (72.295), PI (72.231), MEOU (71.824), and OP (68.696). Greater effort should be concentrated on MU since it has the highest importance (0.281) but low performance (72.558).

7. Discussion and implications

This study was developed in response to the emerging prevalence of QR code m-payment in the retail industry. As hypothesized, the effect of PTC on MU and MU on BI are both positive and significant, supporting H3 and H1 respectively. All in all, these results show that the more benefits offered to the users, the more favorable it is for them to adopt QR code m-payment. One of the benefits is in the form of convenience. This is because it can reduce the queue time when consumers want to make payments, which allows them to save time and perform other activities.

Furthermore, the significant effect of OP on BI was discovered, supporting H5. This is because individuals who have optimistic tendencies towards QR code m-payment have positive perceptions towards it which ultimately affects BI. Additionally, H4 is supported whereby PTS has a significant positive relationship with MEOU. However, H2 and H6 are not supported whereby MEOU and PI do not have significant relationships with BI. This is due to the prior experience that all the respondents have in using m-payment (Ooi et al., 2011). Therefore, they could already have developed the perspective that QR code m-payment is easy to use and thus, do not need to be innovative, unlike in the case of wearable payment (Loh et al., 2019).

Practically, in order to cultivate BI to use, service providers and leading retailers should look into improving the usefulness of QR code m-payment, on top of enhancing convenience and speed during the payment process. All of these could be achieved if a QR code is attached to retailing products. Currently, the bar code that is printed on retailing products has limited functions and does not serve much purpose for consumers. This leads to a slow checkout process in which the retailing products have to be scanned one by one at the counters. If every retailing product comes with a QR code, consumers could enjoy a faster plus convenient checkout process during shopping by scanning the QR codes on the retailing products and paid for them immediately via their m-payment devices. With this, the usefulness of QR code m-payment shall be further elevated as consumers would enjoy the enhanced performance in making transactions. In addition, the use of QR code m-payment in the retailing industry could reduce unnecessary physical interactions between humans and, therefore, increase social distancing to contain the spread of COVID-19 pandemic especially in the absence of vaccines and specific treatment (Anderson et al., 2020; Kasab et al., 2020; Wilder-Smith et al., 2020). The COVID-19 pandemic has created a “new normal”, in which everyone is subjected to a certain degree of constraints in life (Hart, 2020). This “new normal” has delivered many changes to consumer preference, and it was reported that one of the changes is their demands in automation that increases social distancing.

Table 11
Relative segment sizes.

| Number of Segments | Segment 1 | Segment 2 | Segment 3 | Segment 4 |
|--------------------|-----------|-----------|-----------|-----------|
| %                  | 0.519     | 0.217     | 0.157     | 0.107     |

Table 12
R² values for the two-segment solutions.

| Latent Variables | Segment 1 | Segment 2 | Segment 3 | Segment 4 |
|------------------|-----------|-----------|-----------|-----------|
| BI               | 0.392     | 0.627     | 0.909     | 0.815     | 0.865     | 0.712     |
| MEOU             | 0.362     | 0.258     | 0.926     | 0.756     | 0.738     | 0.462     |
| MU               | 0.475     | 0.372     | 0.932     | 0.65      | 0.687     | 0.517     |

Notes:
BI = Behavioral Intention; MU = Mobile Usefulness; MEOU = Mobile Ease of Use.

Table 13
Importance performance map results.

| Latent Variables | Importance (Total Effect) | Performance (Index Value) |
|------------------|---------------------------|---------------------------|
| MEOU             | 0.117                     | 71.824                    |
| MU               | 0.281                     | 72.558                    |
| OP               | 0.258                     | 68.696                    |
| PI               | 0.073                     | 72.231                    |
| PTC              | 0.206                     | 74.865                    |
| PTS              | 0.071                     | 72.295                    |
| Mean Value       | 0.168                     | 72.078                    |

Notes:
MU = Mobile Usefulness; MEOU = Mobile Ease of Use; PTC = Perceived Transaction Convenience; PTS = Perceived Transaction Speed; OP = Optimism; PI = Personal Innovativeness.

PTC shows the highest performance at (74.865), followed by MU (72.558), PTS (72.295), PI (72.231), MEOU (71.824), and OP (68.696). Greater effort should be concentrated on MU since it has the highest importance (0.281) but low performance (72.558).

Fig. 3. IPMA for BI.
(Thomas, 2020). Perhaps, with QR code m-payment in place, consumers do not need to stick in a panic buying queue that compromises all of them within the same retail store during the next pandemic (Peters, 2020; Yang et al., 2020).

Additionally, the service providers and policymakers could emphasize on the optimistic side of QR code m-payment to further cultivate BI to use. This can be carried out by giving incentives to potential mobile users. For example, the Malaysian government gave a one-off RM30 incentive to eligible mobile users in 2020 for encouraging the QR code m-payment adoption in Malaysia (Zahid, 2019). With the correct incentives, mobile users shall be attracted to discover the optimistic side of QR code m-payment.

Theoretically, the framework used in this study was able to yield insightful findings. The proposed model has extended MTAM with four other factors, namely PTC, PTS, OP, and PI. The extension of the MTAM model was based on the suggestions given by several researchers (Phan and Daim, 2011; Benbasat and Barki, 2007). In addition, other researchers further recommended to incorporate variables out of the technological facet for future mobile technology research (Kim et al., 2010; Chen, 2005). This study has reinforced the legitimacy of these suggestions as the theoretical understanding was enriched by the comprehensive findings obtained.

Moreover, based on the Q², the structural model has high predictive relevance. As such, this study posits that the extended MTAM is an effective theory in providing an extensive comprehension of the QR code m-payment adoption. The incorporation of variables besides the technological dimensions has proven to be sound. Overall, the study’s substantial contribution is in theoretical as well as practical terms.

8. Limitations and future directions

The first limitation is the Malaysian context in which this research was carried out in. As such, the results might not accurately match the QR code m-payment adoption scene in other countries as the differentiation between countries is aplenty. These differences could be in the forms of culture, ethnic groups, economic development, and others which could possibly influence technology adoption. Hence, researchers could consider including data from multiple countries by carrying out a cross-country study. Next, in order to address the deficiency of past studies that examined m-payment from a general perspective, this study focused on QR code m-payment. However, this approach neglects the others such as NFC m-payment. Therefore, future researchers can consider conducting a comprehensive study that investigates the different types of m-payment.

Declaration of competing interest

None.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.reteconser.2020.102300.

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