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Bitcoin payment adoption in Taiwanese hotels

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Abstract

This study investigates the factors influencing the intention of hospitality businesses in Taiwan to adopt bitcoin payments. Using the modified Technology Acceptance Model (TAM), the research identifies key determinants including perceived usefulness, perceived ease of use, convenience, and trust. Data collected from 101 Taiwanese hospitality entrepreneurs were analysed using Structural Equation Modelling (SEM). The findings reveal that perceived ease of use has the strongest impact on the intention to adopt bitcoin payments, with convenience also playing a significant role. The study addresses a gap in the literature by focusing on business intentions rather than consumer adoption, providing insights into how hospitality businesses can leverage bitcoin to attract a younger, tech-savvy customer base. However, challenges such as perceived security risks and market volatility remain. The findings offer practical implications for business owners and managers.

Key words: digital payments, blockchain, bitcoin, hospitality

I. Introduction

Since the early 2000s, new technologies, including the Internet, social networks, mobile and electronic payments, have been adopted by millions of business entities, including hospitality businesses (DiPietro and Wang, 2010; Baggio *et al.*, 2020). This adaptation to the new realities of interconnected world is crucial in the aftermath of the global COVID pandemic. As the result of the pandemic, the tourism industry in Taiwan has suffered an enormous blow in 2020. By September 2020, 18 travel agencies in Taiwan filed for temporary closure, and 30 travel agencies filed for corporate dissolution (Yu-Hsin & Xie, 2020). By July 2021, 30% of hotels suspended operations, 30% drastically reduced operations, and the rest were considering one of those two options (Fulco, 2021). Hence, a strategy of adopting new forms of payments might improve robustness of Taiwanese tourism and hospitality industry.

In recent years, bitcoin is gaining momentum as a new form of payment. There are around 46 million bitcoin wallets that hold at least $1 of value. Only around 2% of retailers accept bitcoin payments (Jonker, 2018). At the peak in early 2024 bitcoin market capitalisation was over USD 1.4 trillion (around 1.4% of global GDP in 2022 (World Bank, 2023)). Bitcoin is largely popular among the millennial generation (Bohr et al., 2014). Millennials are becoming an increasingly important customer base for hospitality businesses (DiPietro and Wang, 2010; Lou and Li, 2017; Paul, 2005).

The adoption of bitcoin as legal tender by El Salvador (Renteria et al., 2021) and its acceptance as a form of payment by numerous corporations, such as Microsoft, Paypal, Amazon, Coca Cola, Starbucks, Expedia (Demartino, 2014; Walsh, 2021) demonstrate how bitcoin is changing the existing retail system. Accepting bitcoin payments might turn out to be an effective way for companies to differentiate themselves from the rest (Roussou and Stiakakis, 2016), especially in the eyes of the millennial generation. Similarly, hospitality businesses might also attempt to attract a larger customer base among the younger generation (Wang and Qualls, 2007; DiPietro and Wang, 2010).

On the other hand, as bitcoin is a relatively new invention, the rate of bitcoin payments adoption is still low. Hence, the businesses that are first to start accepting bitcoin will gain a competitive advantage if global rates of bitcoin adoption increase substantially in the future. To shed more light on this process that will likely take place over a number of years, we examine the factors that influence hospitality businesses' intention to accept bitcoin payments. Our focus on the intentions of hospitality business owners' and managers' fills the gap in the existing literature, as the adoption process is not yet well understood and the literature mostly discusses the adoption by users, rather than by businesses (Jonker, 2018; Polasik *et al*., 2015; Schuh and Shy, 2016; Tsanidis *et al*. 2015; Silinskyte, 2014). Our study provides practical benefits to businesses via awareness of the factors to consider when deciding on the adoption of bitcoin payments.

The paper is structured as follows. Section 1 emphasises potential importance and impact of bitcoin payment adoption in the hospitality industry. Section 2 reviews the existing literature and develops the hypotheses regarding the factors affecting the intention to use bitcoin payments. Section 3 involves data analysis and discusses the empirical implications. Section 4 concludes with a discussion of the implications for theory and practice.

II. Literature Review and Hypotheses

Surveying businesses is often more difficult than surveying individual users, most studies on bitcoin adoption focus on users (Yelowitz & Wilson, 2015; Kinney, 2021), creating a gap on merchants' intentions to adopt bitcoin payments (Grover et al., 2019). This study fills the gap and by studying the intentions of the businesses. Our study provides practical benefits to managers, as awareness of the adoption factors might help gain competitive advantage when a larger percentage of young adults own bitcoin. The trend of growing adoption seems to be self-reinforcing as adoption by firms is larger for firms with greater bitcoin knowledge (Polasik et al., 2016).

This study applies the technology acceptance model (TAM) to assessing factors affecting businesses' intention to adopt bitcoin payments. The TAM explains behaviour of adoption of new information technology, mainly via its perceived usefulness (PU) and perceived ease of use (PEU), which are often modelled as mediators of other factors on behavioural intention (Davis, 1989; Munoz, 2008; Lin and Nguyen, 2011; Lou and Li, 2017). Bitcoin's perceived usefulness stems from complete user control over funds, disintermediation, inexpensive transfers, lower merchant's cost, high transaction security, limited supply, international scope.

User control over own funds in bitcoin (which has limited supply) rather than with a financial intermediary, such as a bank, is useful at the time of high inflation or risks of bail-ins (Comfort, Jennen, Valero, 2022). Control over own funds also provides access on weekends or holidays, and even in sanctioned jurisdictions. Bitcoin payments are often cheaper than credit card payments, which cost the merchant around 2.24% fee (Daly, 2023). While bitcoin transaction fees are paid by the buyer, they are cheaper for the user than credit card transactions for the merchant. Hence, tourism businesses might provide discounts for payments in bitcoin vs credit cards. Bitcoin payments are especially efficient versus slow and expensive cross-border bank transfers.

Bitcoin's perceived ease of use stems from its free participation, simple interface, quick transfers, and relative complexity of bitcoin trading. Free participation implies that becoming a bitcoin user is as easy as downloading a wallet application (such as Electrum, Mycelium). Most wallets have a simple interface, with an ability to show the value of bitcoin in fiat currency. Bitcoin transfers take between a few seconds to a few minutes, which is slightly slower than credit card payments. Bitcoin trading might be relevant for a merchant converting the revenue from bitcoin to fiat currency.

In addition to PU and PEU, adoption of bitcoin payments and holding intentions depend on related determinants, such as perceived value, social benefits, convenience (Huang, 2019; Kinney, 2021; Kerviler et al., 2016). Convenience is particularly important for mobile and by extension to bitcoin payments (Teo *et al*., 2015; Kerviler *et al*., 2016). Bitcoin payments are convenience because they (1) remove the need to carry a wallet with cash or credit cards; (2) do not require entering a pin code (as opposed to some credit cards); (3) are readily available as the customers use their phones while waiting in the queue (Boden *et al*., 2020). The convenience of bitcoin payments for the customer can create incentives for hotels (or other vendors) to adopt this type of payment (Boden et al., 2020).

Due to network effect, users' choice to pay with bitcoin depends on acceptance by merchants, which in turn depends on widespread willingness to pay with bitcoin. While network effect is discussed in other payment systems (Dowd & Greenway, 1993; Chakravorti, 2010), it is rarely discussed in bitcoin payments specifically (Luther, 2016). Bitcoin adoption by retailers depends on corresponding desire by their customers, lower transaction costs, and perceived efforts required for the adoption (Jonker, 2018). Network effect accelerates adoption exponentially once some critical mass of early adopters is reached. Bitcoin might still be on the path of reaching the critical mass, especially as a payment method rather than an investment. Schuh and Shy (2016), using the data from 2014 – 2015 Survey of Consumer Payment Choice, show that only about 1% of the respondents own cryptocurrencies. About half of the cryptocurrency owners use them for payments, the other half use cryptocurrencies as an investment.

Despite the usefulness, adopting bitcoin either as investment or as payment system might involve risks. Decentralised nature of bitcoin without a central authority to address grievances implies that bitcoin requires competent control of funds, and that it is not forgiving of errors (Nuryyev et al., 2021). There are numerous examples of users losing their private keys (passwords) and hence access to bitcoin funds (Popper, 2021). In addition to existing technical risks, perceived security (security, risk, trust) and lost value due to bitcoin price volatility are also relevant for bitcoin adoption (Roussou and Stiakakis, 2016; Khalilzadeh et al., 2017). Bitcoin payments are still associated with a relatively high level of perceived risks stemming from lack of understanding of the workings of the decentralised blockchain. New forms of payments are often perceived to be risky, perceived risk affects bitcoin payment adoption (Folkinshtein and Lennon, 2017; Tan, Eze, and Chong, 2009; Wang, Wang, Lin and Tang, 2003).

There are risks, however, outside bitcoin payments as well, for example, the fiat systems constantly face the risk of inflation. Inflation decreases public confidence in financial institutions and increases bitcoin's popularity (Roussou and Stiakakis, 2016, Kinney 2021); especially among the millennial generation (Lou and Li, 2017), interested in transactions without a third party mediation (Kerviler et al., 2016). Since bitcoin emerged independently of any central authority (Nakamoto, 2008), it allows direct electronic transfer of value without the need for third parties, like banks.

Those who have experienced hyperinflation (such as in post-Soviet countries, Venezuela, Argentina, Turkey, etc.) might be more willing to accept bitcoins (Luther, 2016). For example, Venezuela has the third highest cryptocurrency ownership in the world, by percentage of the population (https://triple-a.io/crypto-ownership/). That is largely due to hyperinflation created by loose monetary policy.

Another risk outside of fiat payments is loss of privacy. Bitcoin payment is pseudo anonymous, it does not explicitly identify the payer or the payee, instead the transactions show their bitcoin addresses. Nevertheless, traceability of blockchain might lead to loss of privacy, where the merchant might discover the amount of bitcoins held by the customer. While the privacy issue is easily remedied with a proper use of a bitcoin wallet, the risk of user error is still present.

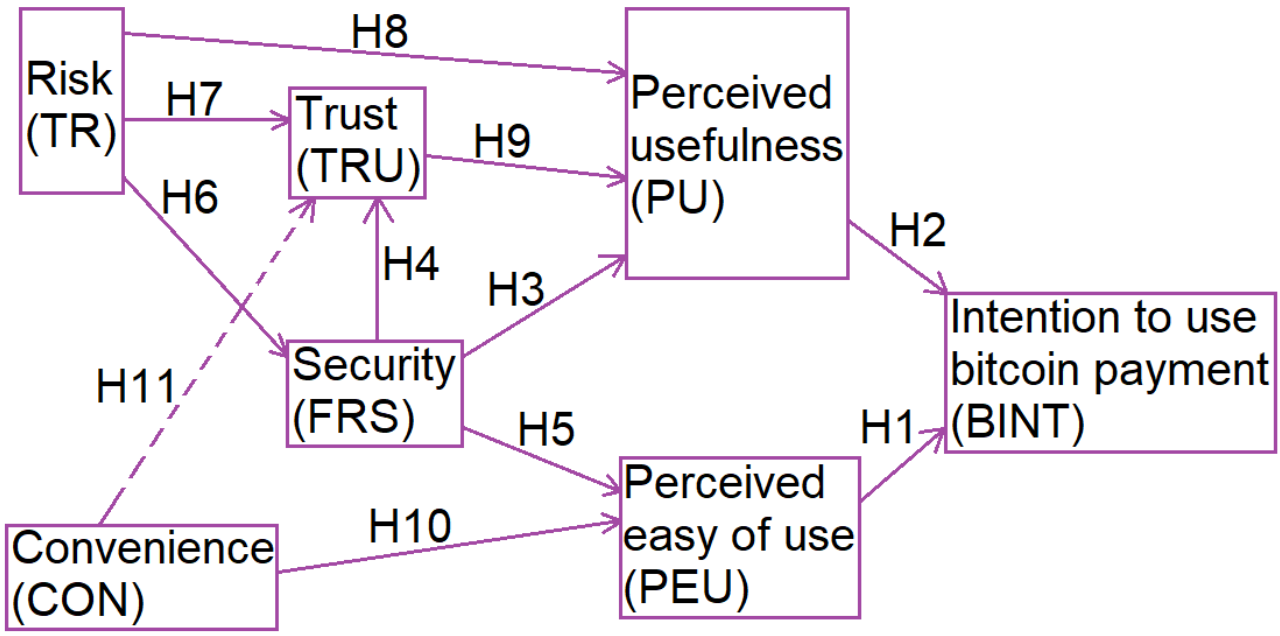
Transactions on the bitcoin blockchain are irreversible. That is because the bitcoin blockchain is decentralised, and reversing a transaction is practically impossible (Nuryyev et al., 2021). This feature might be attractive to the merchants that have experienced fraud via such payment systems as PayPal (Zhou, 2024). Bitcoin is a "push-based" payment system where the user creates a one-time transaction for a specific amount. Without the user creating a new transaction, the merchant cannot take additional payments. The “push-based” system contrasts to “pull-based” payment systems, such as credit cards, where the payer provides the secret card numbers details to the merchant and trusts that the merchant takes the agreed amount (Nuryyev et al., 2021; Folkinshtein and Lennon, 2017). Hence, bitcoin payments might also be attractive to buyers as bitcoin facilitates pseudo-anonymous payments via the internet, without the need to trust the merchant with the credit card details.

State agencies are concerned that the pseudo-anonymity might attract criminals to cryptocurrency payments. Despite the negligible volume of bitcoin being used for criminal activities, occasionally negative media coverage has created a stigma associated with involvement with bitcoin (Kinney, 2021). Criminal activity makes up less than 1% of bitcoin transactions, and criminal activity of all cryptocurrencies combined is much smaller than that of fiat currencies, mostly USD (Lennon, 2021; Yelowitz & Wilson, 2015). Perhaps this stigma is part of the reason why bitcoin is struggling to reach a critical mass that would tip over into faster BTC adoption (Chakravorti, 2010). Some fund managers (Helms, 2021; Shead, 2021) hesitate to include bitcoin in the fund’s investments even while personally investing in bitcoin. Hence, stigma might be easier to overcome for an individual, while companies and merchants are more cautious. Hence, more merchants will be willing to accept bitcoin only after a critical mass of individuals become willing to pay in bitcoin.

There are signs of the emerging critical mass with the recent approval of bitcoin ETFs by the SEC (Securities and Exchange Commission in the United States). This approval also makes bitcoin more trustworthy in the eyes of the general public. Trust is important for acceptance of new technologies (Goles et al. 2009; Yang et al. 2009), especially if they relate to money and payments (Warrington et al. 2000; Misra and Wickamasinghe, 2004). Trust influences intentions to use new forms of payment, and their usefulness (Pavlou, 2003; Shih, 2008). Technology savvy people show higher levels of trust in online applications (Ruiz, Izquierdo and Calderon, 2007; Flavian and Guinaliu, 2007).

Given the existing literature discussed above, this study proposes the following hypotheses that are illustrated in Figure 1 below. Hypothesis H11 illustrated in Figure 1 is based on the data analysis, discussed alongside the hypothesis testing in section III.5.

Figure 1. Illustration of the hypothesized model.


Risk (TR)
Trust (TRU)
Perceived usefulness (PU)
Intention to use bitcoin payment (BINT)
Security (FRS)
Perceived easy of use (PEU)
Convenience (CON)
H1
H2
H3
H4
H5
H6
H7
H8
H9
H10
H11

III. Data Analysis Results and Discussion

1. Descriptive Statistics

The data used in this study was collected through our questionnaire distributed to Taiwanese entrepreneurs in the hospitality industry during the summer 2018. The questionnaire is designed to measure the intention to use/accept bitcoin payments and its determinants. The questionnaire is composed of 36 indicators (items) scored on a 7-point Likert scale from 1 (“strongly disagree”) to 7 (“strongly agree”). These items are adapted from prior studies in related literature on technology acceptance model (TAM) and are grouped into seven sets of indicators, each forming a scale to measure the latent variables in this study, namely, convenience (CON), trust (TRU), perceived risk (TR), perceived security (FRS), perceived usefulness (PU), perceived ease of use (PEU), intention to use cryptocurrency payment (BINT). The questionnaire was answered by 101 entrepreneurs. The demographic description of the sample is shown in Table 1.

Table 1. Demographics

	Number	%
Gender		
Male	62	61.39
Female	39	38.61
Age		
Under 30	29	28.72
30-40	21	20.79
40-50	19	18.81
50-60	26	25.74
Above 60	6	5.94
Education		
High school	8	7.92
Bachelor	64	63.37
Master & PhD	29	28.71
Position		
Employee	40	39.60
Manager & Supervisor	34	33.66
Business owner	27	26.73

2. Methodology

To test our hypotheses, we use Structural Equation Modelling (SEM). The model includes both a measurement part (confirmatory factor analysis, CFA) and a structural part (path analysis). The former describes relations between the latent variables and underlying indicator variables (i.e. the factor structure) and the latter represents the relationships/effects among latent variables as specifies in the hypotheses. To estimate model parameters, standard errors and test statistics, we utilize the lavaan (latent variable analysis) and related R packages (Rosseel, 2012).

The standard estimation method in SEM is based on maximum likelihood (ML) which is based on the assumption that the observed variables are measured on a continuous scale. As our 7-point scale measured variables are ordinal in nature, asymptotic distribution free (ADF) or weighted least squares (WLS) estimator is recommended for parameter estimation in SEM. ADF estimation, however, requires large sample size and performs well only when the model is well-specified (Olsson et al., 2000). Hence, it is common in practice and justified in some academic studies that ordinal variables can be treated as continuous variables in confirmatory factor analysis (CFA). For example, Rhemtulla et al. (2012) suggest that for data sets containing variables with 6–7 categories, simulation results of robust ML and robust WLS methodology for estimating CFA models with ordinal variables were similar for many conditions. Robitzsch (2020) address the rationales to treat ordinal variables as continuous variables on the grounds of validity, reliability, measurement invariance, handling of missing data, and the assessment of global model fit. We therefore considered the 7-point scale data for each measured variable as continuous and use maximum likelihood (ML) method for estimation.

As ML estimation assumes that the data of underlying model follows a multivariate normal distribution, we assess the normality assumption using Shapiro-Wilk univariate normality test and Mardia multivariate normality test. Results from the univariate test show that 36 measured variables do not appear to be normally distributed at the 1% significance level. Results from the multivariate test also indicate that the multivariate normality is rejected at the 1% significance level for both skewness and kurtosis tests.

The ML parameter estimates for non-normal data are still consistent, the standard errors tend to be too small and the ML-based model chi-square statistic tends to be too large. Consequently, the null hypothesis (that a parameter is zero) and the model null hypothesis (that model is fit) tend to be rejected too often (Rosseel, 2012). As our data set is considered as non-normal continuous variables with no missing values, we use MLM estimation method which uses ML to estimate model parameter, but with robust standard errors and a Satorra-Bentler scaled test statistic. Other goodness-of-fit statistics that are a function of the model chi-squared statistic are also based on Satorra-Bentler adjustments.

3. Assessment of Measurement Properties

We begin to fit a CFA model with initial 36 measured variables using standardized solution. Setting the variances of all variables (both indicator and latent) to the standardized value of one allows us to have standardized coefficients (factor loadings) of each of the indicators on the same latent variable. This allows for direct comparison of the strength of relationships between different indicators and latent factors within the model. The standardized loading can be interpreted as indicating how many units of standard deviation in the indicator variable will change for one standard deviation change in the latent variable.

To assess the measurement properties of latent variables in the initial CFA model, we use statistics related to reliability, convergent validity, and discriminant validity, such as Cronbach's alpha, omega composite reliability, factor loadings, average variance extracted (AVE), and correlations between latent variables. A recent review of this topic can be found in Cheung et al. (2023).

Reliability in internal consistency of items is assessed by Chronbach's alpha, which assumes equal factor loadings across items within the same test, and by Composite Reliability (CR) or Omega, which does not require equal factor loadings. Chronbach's alpha values of all tests (sets of indicators) are well above the conventional cutoff value 0.7. However, the item-test and item-rest correlations of pu4 is much lower than those of the other items for the latent variable PU indicating that it does not seem to fit well in the scale. Composite Reliability (CR) are also all greater than 0.7 (Hair et al., 2009).

To check convergent validity, we examined standardized factor loadings and average variance extracted (AVE). Standardized factor loadings, except that of pu4, are all statistically significant from zero at 1% significance level with values well above 0.7, meaning that each latent variable explains at least 49% of the variance of each indicator. AVE values of all latent variables are greater than threshold of 0.5, indicating that the latent variables all explain no less than 50% of the indicator variance (Fornell & Larcker, 1981).

The discriminant validity is assessed by whether the correlation between two latent variables is less than 0.9 (John and Benet-Martinez, 2000), whether AVE is greater than shared variance or squared correlations (Fornell & Larcker, 1981) and whether Heterotrait-monotrait (HTMT) ratio is less than 0.9 (Henseler et al., 2015). All correlation coefficients between paired latent variables are less than 0.9, indicating that latent variables are distinct. The AVE values of all latent variables (except for PU) are all smaller than 0.9. Three out of twenty-one HTMT ratios are greater than the shared variance (i.e., squared correlation). HTMT ratio compares the correlations between indicators of different constructs to correlations within the same construct. Three out of 21 HTMT ratios are greater than 0.9 (TRU-PU, PEU-PU, BINT-PU). Therefore, there are discriminant validity problems with some latent variables.

We also examine the variance-covariance matrix of standardized residuals (SR). About 7% (44 out of 630) of SR have absolute value greater than 2.58 at about 1% significance level. Some items have multiple significant SR with other indicator variables, which may arise from the redundancy of indicator variables with similar wording for respondents. To improve the measurement properties, we drop five items with reliability and discriminant validity concerns: con4, tr2, pu4, pu5, pu6. The modified indices form the initial CFA model suggest that some problematic indicators (bint4, peu3, tru7) can be dropped to improve model fit while ensuring at least 3 items remaining for each latent variable for identification. These items were excluded from the research model. The reliability, convergent validity, and discriminant validity testing results of the modified model are shown in Table 2. According to the preceding criteria, Table 2 exhibits acceptable measurement properties of the modified model with 28 remaining items.

Table 2. Reliability, convergent validity, discriminant validity (modified model)

Latent variables	Indicator variables	Range of standardized loadings	Alpha	Omega	AVE	Range of SC	Range of HTMT
CON	con1, con2, con3	0.961 - 0.888	0.953	0.952	0.871	0.008 - 0.706	0.087-0.818
TRU	tru1, tru2, tru3, tru4, tru5, tru6	0.940 - 0.861	0.970	0.970	0.843	0.040 - 0.635	0.187-0.806
TR	tr1, tr3, tr4, tr5, tr6, tr7	0.809 - 0.942	0.960	0.962	0.804	0.001 - 0.676	0.049-0.828
FRS	frs1, frs2, frs3, frs4	0.962 - 0.878	0.954	0.952	0.837	0.033 - 0.676	0.155-0.828
PU	pu1, pu2, pu3	0.896 - 0.902	0.927	0.926	0.808	0.001 - 0.553	0.049-0.748
PEU	peu1, peu2, peu4	0.784 - 0.971	0.930	0.939	0.831	0.028 - 0.789	0.118-0.885
BINT	bint1, bint2, bint3	0.898 - 0.954	0.949	0.941	0.854	0.031 - 0.789	0.166-0.885

Note: Alpha = Chronbach’s alpha; SC = squared correlations with latent variables.

4. Assessment of Measurement Model (CFA Model)

The null hypothesis is that a specified CFA model provides a good fit to the observed data in the sense that the difference between the model implied and actual covariance matrices is not significant. Traditionally model fit will be assessed collectively by chi-square test and other model fit indices, including root mean square error of approximation (RMSEA), Comparative Fit Index (CFI) and Tucker–Lewis index (TFI) and the standardized root mean square residual (SRMR).

Various guidelines on interpretation of model fit indices have been proposed. For example, Hu and Bentler (1999) recommend using one of the relative fit indices (e.g. CFI) close to .95 or higher, in combination with one of the two absolute fit indices, either RMSEA or SRMR, less than .08 or .06, respectively for a good model fit. Yuan et al. (2016) propose cut-off values for RMSEA (.01, .05, .08, and .10) and TLI (.99, .95, .92, and .90) to distinguish five level of model fit, namely, excellent (RMSEA<.01, TLI > .99), close (RMSEA= .01-.05, TLI=.95-.99), fair (RMSEA= .05-.08, TLI=.92-.95), mediocre (RMSEA= .08-.10, TLI=.90-.92), and poor (RMSEA >= .10, TLI<0.90). In this study we use these guidelines for the model’s goodness of fit.

We examine the variance-covariance matrix of standardized residuals for local model fit. Only four out of 378 standardized residuals (or 0.11%) of SC have absolute value greater than 2.58, a dramatic decrease from that in the initial CFA model. The global model fit indices of the modified CFA model are shown in Table 3a. The Satorra–Bentler scaled chi-squared statistic is 403.140 (degrees of freedom=329) with a p-value of 0.000 and a scaling factor of 1.569. Scaled RMSEA statistic is 0.059 with the 90% CI [0.036,0.078], Scaled CFI and TLI are 0.969 and 0.964, respectively. The SRMR is 0.050. We conclude that the modified CFA model had a fair and acceptable fit.

Given the acceptable model, we examine standardized factor loading of the modified CFA model as summarized in Table 2. Standardized factor loadings ranged from 0.784 to 0.971, indicating that the magnitude of the relationships between items and factors were adequate (greater than 0.7). All the coefficients are different from zero at 1% significance level. The R square values for each item, which are the squared standardized loadings of items, indicate that the percentage of the item variance explained by the corresponding latent variable ranged from 61% to 94%.

Table 3a. Fit Statistics of CFA

Model	$\chi 2$ (df), p_value	$\chi 2$_SB (df), p_value	$\chi 2$ Scaling Factor	RMSEA_SB	RMSEA_SB 90% CI	SRMR	CFI_SB	TLI_SB
CFA_initial	1373.835(573) 0.000	813.074(573) 0.000	1.690	0.064	(0.056,0.072)	0.084	0.917	0.909
CFA_modified	632.494(329) 0.000	403.140(329) 0.000	1.569	0.059	(0.036,0.078)	0.050	0.969	0.964

5. Assessment of Structural Model and Hypothesis Testing

We continue with the modified model as its fit is acceptable. Next, we model the effects among latent variables in order to test our hypotheses (structural model). We run a full SEM model with both its measurement and structural parts (path analysis). The results of the initial SEM model are shown in Table 3b. The model fit statistics are inferior to the corresponding CFA model (CFA-revised) and suggest a poor fit. In particular, the SRMR of the modified SEM model is 0.265, indicating that the structural model may be mis-specified. The modification indices suggest that a path from the latent variable CON to TRU may be added. As it would be justified conceptually, we modify the structural model by including an additional path from the latent variable CON to TRU. The fit indices of this final SEM model are presented in Table 3b. The Satorra–Bentler scaled chi-squared statistic is 437.235 (degrees of freedom=338) with a p-value of 0.000 and a scaling factor 1.542. Scaled RMSEA statistic is 0.067 with the 90% CI [0.047,0.084], Scaled CFI and TLI are 0.959 and 0.954, respectively. SRMR is 0.081, which is marginally above the cut-off of 0.08. Based on this set of fit statistics, we concluded that the final SEM model has an acceptable fit.

Table 3b. Fit Statistics of SEM

Model	$\chi 2$ (df), p_value	$\chi 2$_SB (df), p_value	$\chi 2$ Scaling Factor	RMSEA_SB	RMSEA_SB 90% CI	SRMR	CFI_SB	TLI_SB
SEM_modified	765.239(339) 0.000	504.238(339) 0.000	1.518	0.086	(0.070,0.101)	0.265	0.933	0.925

SEM_final	674.413 (338) 0.000	437.235 (338) 0.000	1.542	0.067	(0.047,0.084)	0.081	0.959	0.954

Given the acceptable model, we examine various parameter estimates. Standardized factor loadings of the final SEM model are qualitatively and quantitatively similar to those reported in the modified CFA model in Table 2. The standardized regression coefficients, representing relationships between independent latent variables and the dependent variables, are shown in Table 4. A graphical representation of the full model is depicted in Figure 2.

The analysis of standardized path coefficients shows that four out of the originally proposed ten hypotheses are supported at the 1% significance level (H1, H6, H9, H10), two supported at the 5% significance level (H2, H5), and one supported at the 10% significance level (H4). Both PU and PEU positively and significantly influence BINT (H1, H2). Furthermore, PEU has a much larger and stronger impact on BINT (a coefficient of 0.806) than PU does (a coefficient of 0.153). This may be attributed to the fact that our respondents are not general investors in cryptocurrencies who care more about investment returns. As businessmen, however, they focus more on whether the use of cryptocurrency payments can facilitate and boost their hospitality business. FRS has a positive and significant impact on both TRU and PEU (H4, H5), while its effect on PU (H3) is rejected at the 10% significance level. As expected TR has a substantial negative impact on FRS (H6). However, TR's influence on TRU and PU is not supported with either being insignificant (H7) or significant in the wrong sign (H8). As predicted, CON has a positive and substantial impact on PEU (H10).

In this study our data indicate that CON may have a substantial and positive influence on TRU (H11). Given the high coefficient on CON->PEU (0.805) and PEU->BINT (0.806), our model suggests that convenience (CON) has a dominant influence on the adoption of cryptocurrency payments by hospitality businesses in Taiwan. The result may reflect the tendency that convenience is highly valued in every aspect of daily life in Taiwan.

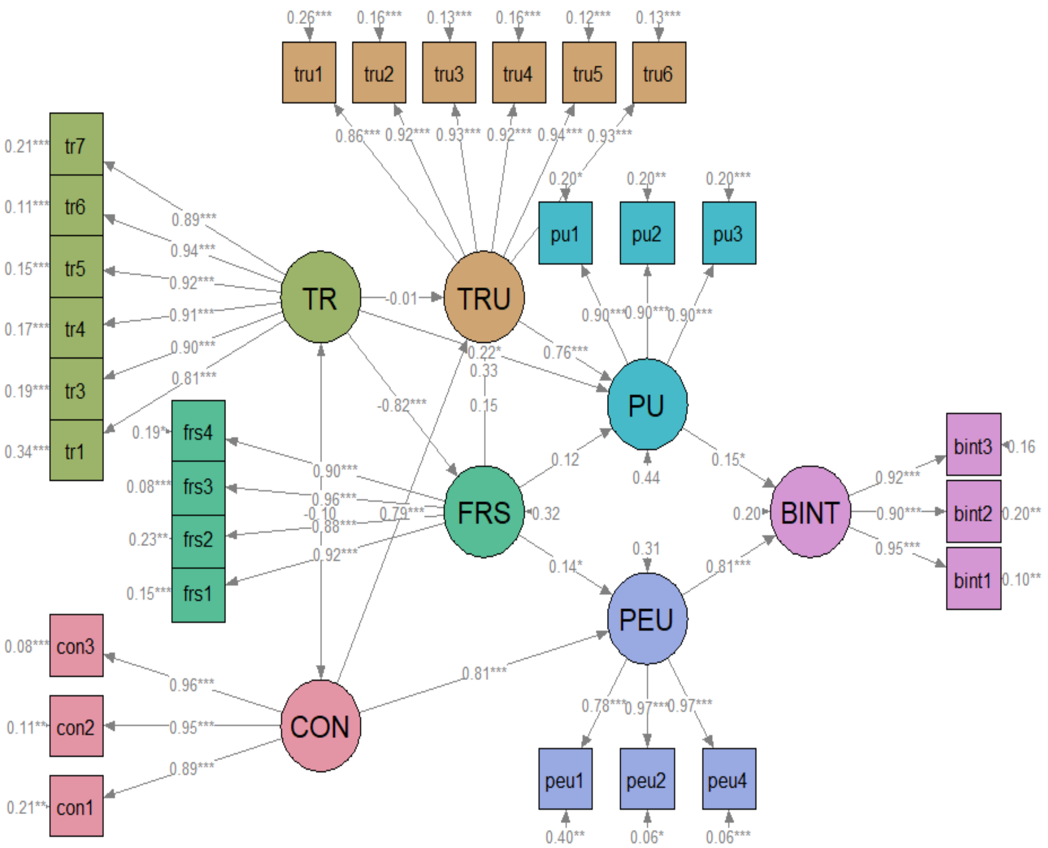
There are two paths that CON can indirectly influence BINT, namely CON->PEU->BINT and CON->TRU->PU->BINT. We further analyse the total indirect effect of CON on BINT. We compute the indirect effects and their percentile confidence intervals using bootstrap method with 5000 samples (Cheung and Cheung, 2023). The indirect effect from CON to BINT through PEU is 0.649, with a 95% bootstrap confidence interval of [0.479 to 0.804]. The indirect effect from CON to BINT through TRU and PU is 0.091, with a 95% bootstrap confidence interval of [-0.036 to 0.232]. The total indirect effect of CON on BINT is 0.741, significantly different from zero at 5% level, with a bootstrap confidence interval of [0.609 to 0.832]. Therefore, the major impact of CON on BINT is channelled through PEU instead of PU.

As a robustness check, we compared the results of the final SEM with the results of the initial model that includes all the indicator variables. The findings were qualitatively similar in terms of hypothesis testing, with one notable difference: the impact of perceived ease of use (PEU) on the intention to use cryptocurrency payment (BINT) remained dominant, albeit with a weaker effect observed in the initial model. To conclude, the major findings of our model is that perceived ease of use has the strongest direct effect on the acceptance of cryptocurrency payment, which in turn is heavily influenced by the perceived convenience of entrepreneurs in Taiwan hospitality industry.

Table 4: Structural Path Coefficients

Hypothesis	Predicted Sign	Path Coef.	Std. Err.	z	P>z	Supported
H1: PEU -> BINT	+	0.806	0.049	16.302	0.000	Yes***
H2: PU -> BINT	+	0.153	0.065	2.333	0.020	Yes**
H3: FRS -> PU	+	0.117	0.089	1.312	0.189	No
H4: FRS -> TRU	+	0.154	0.088	1.740	0.082	Yes*
H5: FRS -> PEU	+	0.142	0.060	2.382	0.017	Yes**
H6: TR -> FRS	-	-0.822	0.078	-10.547	0.000	Yes***
H7: TR -> TRU	-	-0.006	0.085	-0.066	0.947	No
H8: TR -> PU	-	0.218	0.094	2.328	0.020	No**
H9: TRU -> PU	+	0.758	0.051	14.820	0.000	Yes***
H10: CON -> PEU	+	0.805	0.046	17.682	0.000	Yes***
H11: CON -> TRU	?	0.789	0.045	17.622	0.000	Yes***

Figure 2. SEM model of the factors affecting bitcoin payment adoption.



IV. Conclusion

This study provides valuable insights into the factors influencing the intention of hospitality businesses in Taiwan to adopt bitcoin payments. The findings underscore the importance of perceived usefulness, perceived ease of use, convenience, and trust as critical determinants in the decision-making process. By applying the Technology Acceptance Model (TAM) to this specific context, we shed light on the ways in which these factors interact to influence business decisions. We contribute to the existing literature by filling the gap regarding business intentions towards bitcoin adoption, a topic that has been predominantly user-focused in previous studies.

The adoption of bitcoin payments presents opportunities as well as challenges for the hospitality industry, especially in appealing to younger and tech-savvy customers that values innovation and control over their financial transactions. Adoption of bitcoin payments, however, is not without risks, particularly in terms of perceived security, volatility, and the associated stigma. The findings suggest that bitcoin payments gaining traction within the hospitality sector is likely contingent on overcoming these barriers and reaching a critical mass of willing users and businesses.

As bitcoin and other cryptocurrencies continue to evolve, future research could explore longitudinal studies to assess how these factors change over time and whether early adopters of bitcoin payment systems in the hospitality industry gain a significant competitive advantage. Additionally, further studies could examine the impact of regulatory changes and technological advancements on the adoption process.

Overall, this study provides a foundational understanding of the key drivers behind bitcoin payments adoption in the hospitality industry and offers practical implications for business owners and managers.

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