A Utility Theory Model for Individual Adoption of Bitcoin

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Abstract
In recent years, the growth of cryptocurrency prices, notably that of Bitcoin has garnered mainstream news coverage. However, very little is known about the factors that motivate an individual to adopt Bitcoin, though studies abound in the blockchain technology adoption and its use in various domains such as healthcare, supply chain, and finance. In the current paper, we argue that the existing, widely-used IT adoption models may not thoroughly explain the reasons (i.e., benefits, barriers, and specific factors) associated with the adoption of cryptocurrencies. We propose a research model based on UTAUT and utility theory to discover the perceived benefits, perceived risks, facilitating conditions, and social effects in the individual adoption of Bitcoin.

Keywords: Blockchain, Bitcoin, Adoption, Privacy, Multimethod Research, Construct Development
A Utility Theory Model for Individual Adoption of Bitcoin

1. Introduction
Cryptocurrency adoption for individual activities remains a central concern of governments, the fintech (financial technology) industry, electronic commerce businesses, information systems (IS) researchers, and practitioners. Despite impressive advances in hardware (e.g., Powerful chips, ASIC design, and exchanges) and software capabilities (e.g., cryptography, software, and mass use of software in phones and computers) and computer networks, individuals can render financial transactions legally at almost negligible fees. Cryptocurrency systems are vastly underutilized but may have huge potential in the future (DeVries, 2016). The low usage of Bitcoin and other cryptocurrencies has been identified as a pressing concern with the blockchain sector (Hayes, 2017). Understanding and creating the conditions under which individuals and businesses will embrace cryptocurrency, and related systems such as payment gateways, electronic wallets, and vendor systems remains a high-priority research issue. How to facilitate a digital economy that provides financial access to the excluded is also a prominent research issue (Cousins, Subramanian, & Esmaeilzadeh, 2019).

Information Systems (IS) researchers have made significant progress in studies on the user acceptance of different types of information technology systems within organizations. This stream of research began with the Technology Acceptance Model (TAM) (Davis, Bagozzi, & Warshaw, 1989) and its variants. This effort was followed by the unified theory of acceptance and use of technology (UTAUT) (Venkatesh, Morris, Davis, & Davis, 2003), the Theory of Reasoned Action (Fishbein & Ajzen, 1975) and the Theory of Planned Behavior (Ajzen, 1991). We conducted a multi-period multimethod study to discover the factors that influence an individual to adopt Bitcoin. Using a sequential approach, we conducted a qualitative research study followed by a quantitative research study over four years from 2016 to 2019. It is important to note that during this period, Bitcoin’s price was highly volatile, and by being a fringe economy instrument, every major government and business in the world has actively been affected by Bitcoin. We investigated the following two research questions; 1. “What factors influence an individual’s adoption of Bitcoin? and 2. “How do these factors influence an individual’s adoption of Bitcoin?”.

2. A Multi-Method Research Design
A combination of qualitative and quantitative data collection and analysis methods were used on separate samples to examine Bitcoin adoption and usage. We conducted email interviews with one sample of users and non-users, followed by a survey study on a different sample. In line with prior multimethod studies (Mingers, 2003; Spears & Barki, 2010), we chose this multimethod approach based on the premise that separate and dissimilar data sets drawn on the same phenomena would provide a richer picture of the concepts and outcomes associated with Bitcoin adoption and use than would require a mono-method approach. Accordingly, we used a sequential design where a qualitative exploratory study informed a subsequent confirmatory survey. Thus, by combining qualitative and quantitative methods, we strengthened the results through triangulation and cross-validation across multiple samples and sources of data. Figure 1 describes the sequential design of our research study.
3. Study 1: An Exploratory Study of Bitcoin Adoption and Use
First, we develop a conceptual definition of the constructs because the lack of a precise and detailed conceptualization of the focal constructs can cause significant measurement errors during the testing phase (MacKenzie et al., 2011).

3.1 Data Collection
To conduct the exploratory study, we interviewed three groups of informants over three phases of data collection between 2016 and 2018. These three groups of informants included (1) Bitcoin experts, including early adopters, (2) Bitcoin users and non-users, and (3) Bitcoin stakeholders. This approach allowed us to triangulate our results across three groups of informants to explore Bitcoin adoption issues from various perspectives. In phase 1, our objective was to understand the perceptions of Bitcoin innovators who were early adopters – a group we referred to as Bitcoin experts. To achieve this goal, we conducted a focus group study where we interviewed 12 key members of a recognized Bitcoin meetup group in the southeastern United States (U.S.), who organized meetings through the website of meetup.com.

In phase 2, we were particularly interested in expanding our analysis to a larger population to understand general attitudes towards Bitcoin. Therefore, using a convenience sampling approach, we decided to interview 110 randomly chosen students enrolled in MBA and BBA programs at a large southeastern U.S. university. These students were both users and non-users of Bitcoin (who were familiar with Bitcoin but did not practically use it by the time of the survey). Using Qualtrics software, we emailed the interview protocol to these interview subjects. The interview protocol was designed around three main open-ended questions 1. Compared to traditional payment methods (such as cash, credit card, debit card) or other online payment systems (such as Paypal), what do you think as the possible advantages of using Bitcoin? 2. Compared to traditional payment methods (such as cash, credit card, debit card) or other online payment systems (such as Paypal), what do you think as the possible barriers of using Bitcoin? 3. Considering both drivers and barriers of Bitcoin, will you use Bitcoin in your transactions in the future?

In phase 3, we wanted to understand how Bitcoin’s stakeholders perceived Bitcoin. Our main criteria for identifying stakeholders were: (a) they were professionals engaged with the crypto-ecosystem on a day-to-day basis in one role such as miners, investors, application developers, media practitioners, or researchers; and (b) they understood the technology.
3.2 Data Analysis

The primary goal of the data analysis was to construct development and hypothesis development. This step was a sequential process involving; (1) construct development, (2) identification of Bitcoin’s positive and negative utilities, and (3) hypothesis development. In qualitative data analysis, classification and connection of constructs from the basis of theory development. Seeing that we had no a priori theoretical framework or coding schema, we used grounded theory techniques to analyze the data. To guide this process, we posed the following questions: 1. What are the main benefits of Bitcoin (positive utilities) use suggested by the interviewees? 2. What are the key challenges (negative utilities) associated with Bitcoin use suggested by the interviewees? 3. What are the main social factors affecting the adoption of Bitcoin indicated by the interviewees?

These questions were used to systematically review and code the interviews. We use open, axial and selective coding procedures suggested by Strauss and Corbin (1990) to identify conceptually similar themes mentioned by the interviewees. Open coding is an analytical process, which involved identifying concepts, properties, and dimensions. Axial coding involves relating categories to their subcategories. Selective coding represents the final stage of data analysis to be completed after core concepts that emerged from the coded data categories have been identified through open and/or axial coding. These selective codes represent theoretical constructs. We used open coding and axial coding techniques to identify constructs, which represented Bitcoin’s key characteristics and features. We then used cluster analysis to group the axial codes representing the identified constructs into selective codes. These selective codes represented Bitcoin’s positive and negative utilities. The next step of the analysis involved developing selective codes representing the positive and negative utilities associated with Bitcoin.

3.2.1 Identification of Bitcoin’s Positive and Negative Utilities

The axial codes we identified represent features interviewees believed represented Bitcoin’s benefits and challenges related to use behaviors. Table 1 shows the results of cluster analysis:

<table>
<thead>
<tr>
<th>Positive Utilities</th>
<th>Percentage (%)</th>
<th>Negative Utilities</th>
<th>Percentage (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Anonymity</td>
<td>90%</td>
<td>Physicality</td>
<td>85%</td>
</tr>
<tr>
<td>Universality</td>
<td>98%</td>
<td>Volatility</td>
<td>98%</td>
</tr>
<tr>
<td>Investment opportunities</td>
<td>91%</td>
<td>Traceability</td>
<td>90%</td>
</tr>
<tr>
<td>Ease of use</td>
<td>93%</td>
<td>Potential scams</td>
<td>95%</td>
</tr>
<tr>
<td>Transaction time</td>
<td>90%</td>
<td>Irreversibility</td>
<td>89%</td>
</tr>
<tr>
<td>Transaction cost</td>
<td>91%</td>
<td>Technical flaws</td>
<td>91%</td>
</tr>
<tr>
<td>Regulation issues</td>
<td></td>
<td></td>
<td>96%</td>
</tr>
</tbody>
</table>
3.2.2 Second-order constructs

The second-order constructs and their definitions are shown in Table 2.

<table>
<thead>
<tr>
<th>Second-order construct</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Positive utilities</td>
<td>The degree to which an individual perceives benefits from the adoption of Bitcoin.</td>
</tr>
<tr>
<td>Negative utilities</td>
<td>The degree to which an individual perceives risks from the adoption of Bitcoin.</td>
</tr>
<tr>
<td>Social effects</td>
<td>The degree to which an individual perceives social pressures to adopt Bitcoin.</td>
</tr>
<tr>
<td>Structural provision</td>
<td>The degree to which an individual perceives support and facilitating infrastructure for the adoption of Bitcoin.</td>
</tr>
<tr>
<td>Personality traits</td>
<td>The degree to which an individual perceives that he/she is confident in his/her ability to adopt Bitcoin.</td>
</tr>
</tbody>
</table>

3.2.3 Measure Development

The second step is the creation of items for the defined constructs. During the item development, the codes derived from the qualitative study were leveraged. We also searched the literature for previous studies that may have used similar constructs to identify items that may be relevant to the context of this research. Altogether, 112 items were initially developed to capture the essential aspects of the constructs. Then, we asked two Ph.D. and four Masters students to perform the face validity check. The participants in the face validity check were familiar with how the Bitcoin ecosystem works. They were asked to comment on the clarity of the questions. Totally, 13 items were reported as confusing or vague. Two of them remained after modifying the wording. As a result, a pool of 101 items was used in the next step.

3.2.4 Content validity assessment

According to MacKenzie et al. (2011), content validity explains whether a scale represents all aspects of a given construct. To perform this assessment, two measures should be taken: (1) each item represents a facet of the construct’ content. (2) all the items together are representative of the entire domain of the construct. To do so, we followed the procedure suggested by Anderson and Gerbing (1991). Based on this approach, each item should represent a single construct. Since some constructs are developed by the authors, we mainly used content validity check to identify potentially overlapping across constructs. Due to the number of items and constructs and to avoid confusion, we used several matrix tables on Qualtrics to place items in the rows and list construct definitions at the top of the columns. We grouped the first-order constructs in one matrix to identify potential overlap across these constructs. Then, we asked 183 independent raters (Bachelors’ students) to assign each identified items to one construct definition.

To check the content validity, we computed two indexes: the proportion of substantive agreement (PSA) and the substantive validity coefficient (CSV). PSA refers to the proportion of raters who assign items to their posited constructs, and CSV indicates whether raters assign items to the intended construct rather than to any other construct (Anderson & Gerbing, 1991). As recommended in other studies (Hoehle & Venkatesh, 2015), we used a threshold of .60 as a cutoff point for both indexes’ values. This cutoff value suggests that
more than 60% of all respondents assign the items to the intended construct definitions. The values for PSA ranged between 0.69 and 0.91, and the values for CSV ranged between 0.72 and 0.87. Results show that the content validity ratios for all the 101 items met the .60 cutoff value, which implies that most raters associated the majority of items with their intended construct domains.

### 3.2.5 Measurement Model Specification

In this step, using a measurement model, we show the indicators relate to the constructs as well as the relationships between the first-order and second-order constructs. Our proposed measurement model is excluded from our discussion in this submission. In this study, we discuss that because positive utilities, negative utilities, social effects, structural provision, and personality traits do not exist independent of their components, and these components are not conceptually interchangeable, modeling these constructs as formative is more appropriate (Huang, Chengalur-Smith, & Pinsonneault, 2019). Since these components conceptually tap into different aspects of structural capital, and they are not expected to necessarily covary, making these constructs formative is appropriate.

### 4. Research Model

In order to develop a framework for this study, we used both UTAUT and utility theory as a base. The resulting research model, which is mainly based on a belief-attitude-intention framework proposes several causal relationships. The primary five constructs used to develop the model are positive utilities, negative utilities, social effects, structural provision, and personality traits. In this section, we articulate how these constructs may influence individuals’ attitudes toward Bitcoin and their willingness to use it in the future. Figure 2 describes the key testable hypotheses and relationships among constructs.

![Research Model Diagram](image)

**Figure 2: Research Model**

### 5. Study 2: A Confirmatory Study of Bitcoin Adoption and Usage

#### 5.1 Pretest Study

The next step is the pretest of the survey instrument. In this step, the convergent, discriminant, and nomological validity of the scales should be investigated (Straub, Boudreau, & Gefen, 2004). Before data collection, we asked four Ph.D. students to read the
survey, complete it, and provide feedback on the items and survey structure. Only minor changes (e.g., pagination, change of terms) were proposed by these students, and they confirmed that the instructions were clear and easy to understand. We aimed to collect more than 500 responses that are necessary to investigate the psychometric properties of the scales (Hair, Black, Babin, Anderson, & Tatham, 2006).

5.2 Scale Purification and Refinement

In this step, we used the pretest data to refine the survey instrument. The authors discussed in some rounds to refine the survey instrument, test the reliability of these measures, and find the unique proportion of variance in second-order constructs. We also assessed the item loading for the first-order constructs and the weights of each first-order construct on the intended second-order construct. Table 12 shows that all item loadings are above 0.70, which also supports convergent validity. The weights of the first-order formative constructs on the intended second-order constructs were significant (p < .001). This finding supported that each first-order construct significantly contributed to the respective second-order construct. Then, we checked for multicollinearity by computing the variance inflation factor (VIF) for all first-order constructs forming the second-order constructs. The resultant VIF values are between 1.62 and 3.83, which are below the cutoff value of 4 (Petter, Straub, & Rai, 2007). Thus, multicollinearity is not an issue in this research. Since all these findings were promising, we did remove any items from the instrument.

5.3 New Sample Data Collection: The Main Study

Once the scales are pretested and refined, a new sample data collection should be performed to re-assess the purified scales. To ensure that we collected data from a new sample, we designed and used an online version of the questionnaire (custom-developed using Qualtrics software) and utilized the Amazon’s Mechanical Turk (MTurk) platform to survey a national sample of patients. MTurk has been used in several studies as a reliable and acceptable source of subject participants (Marge, Banerjee, & Rudnicky, 2010) to analyze the perceptions of samples that are quite representative of the general population of interest, including a broad range of ages, income levels, ethnicities and work experiences (Behrend, Sharek, Meade, & Wiebe, 2011). The incentive for participation was a monetary reward ($1). Since the main objective of this study is to examine factors shaping individuals’ perceptions about Bitcoin and investigate their willingness to use Bitcoin, we used a clear explanation to educate our potential respondents about Bitcoin. Thus, at the beginning of the survey, a detailed description of “what Bitcoin is and how it works” was provided to ensure that respondents completely comprehended the context and purpose of the study. Totally, 843 individuals within the U.S. attempted the survey.

As mentioned in previous studies, one general concern in data collection is the potential lack of attention and random responses (Huang, Curran, Keeney, Poposki, & DeShon, 2012). Consistent with other studies, we used “captcha” questions to prevent and identify careless, hurried, or haphazard answers (Mason & Suri, 2012). Based on answers to these questions, thirty-one responses were dropped. Previous studies that collected data using MTurk reported a similar ratio of dropped responses (O’Leary, Wilson, & Metiu, 2014). Thus, concerns that online respondents might reply randomly or haphazardly to complete the survey quickly were alleviated. The responses that failed the quality assessment were excluded, and the final set of usable responses that could be used in the study comprised of 812 samples. The average time for survey completion was found to be 15.18 minutes. With regard to the time spent on completing the survey and the number of questions included in the questionnaire, the mean response time implies that the answers can be acceptable.
The demographic characteristics show that the majority of respondents were female (52%), White (52%), with a full-time job (67%), had a bachelor’s degree (43%) and aged between 20-29 years old (52%). All participants lived in the U.S. at the time of data collection, and most of them resided in suburban areas (47%). About their technology experience, around 72% reported that they were extremely comfortable with computers, and 82% stated that they were extremely comfortable with the Internet, and 89% of respondents rated their computer skills either good or excellent. Finally, the majority of participants (62%) did not use any forms of cryptocurrencies, and among those who used cryptocurrencies before 72% used Bitcoin.

6. Results: Structural Model Analysis
The hypotheses were tested using IBM SPSS AMOS (Version 22) within a Structural Equation Modeling framework. Ho (2006) notes that the overall fit of the structural model can be assessed using the goodness of fit indices. The findings indicated that the χ² of the model was 11757.273, with 5231 degrees of freedom (χ²/df = 2.24). The indices values for GFI= 0.951, AGFI= 0.90, CFI = 0.920, NFI= 0.916, RFI= 0.917, and TLI= 0.934 were above 0.9 and the SRMR = 0.033 and RMSEA= 0.045 were below 0.08 (Byrne, 2001). The values of all these indices were found to be in the acceptable range. As the results indicate, at least four indices met the minimum recommended values, supporting a good fit between the observed data and hypothesized model following Kline (2015).

The results of the hypotheses testing are summarized in Table 3. H1a is not supported where there is no evidence found to support that perceived anonymity leads to an enhanced attitude toward using Bitcoin (β = 0.006, non-significant). Support is also not found for H1b, which indicates that perceived universality would significantly reinforce attitude toward using Bitcoin (β = 0.043, non-significant). H1c, which posits that perceived investment would directly affect attitude toward using Bitcoin, is supported (β = 0.656, p < 0.001). The analysis demonstrates that individuals’ perceived ease of use positively influences their attitude toward using Bitcoin (β = 0.165, p < 0.01), and this positive relationship supports H1d. Support is also found for H1e, which argues that attitude toward Bitcoin would be positively influenced by perceived transaction time (β = 0.122, p < 0.01). Moreover, results provide evidence to support H1f, which posits that perceived transaction cost would enhance an individual’s attitude toward using Bitcoin (β = 0.079, p < 0.05).

The path coefficient of the relationship between perceived physicality of Bitcoin and attitude toward using Bitcoin is significant, supporting H2a but in the reverse direction (β = 0.163, p < 0.001). Moreover, the effect of the perceived volatility of Bitcoin on attitude toward using Bitcoin is significant, supporting H2b (β = -0.144, p < 0.05). H2c argues that there exists a negative relationship between the perceived traceability of Bitcoin transactions with attitude toward using Bitcoin, which is not supported (β = -0.098, non-significant). The results provide evidence to support H2d, which indicates that perceived potential scams could negatively influence attitude toward using Bitcoin (β = -0.079, p < 0.01). H2e posits that there is a negative relationship between perceived irreversibility of Bitcoin transactions and attitude toward using Bitcoin, which is not supported (β = -0.037, non-significant). Support is also found for H2f, which indicates that perceived technical flaws would exert a negative effect on attitude toward using Bitcoin (β = -0.175, p < 0.001). H2g is supported where evidence found to support that perceived regulations associated with Bitcoin lead to unfavorable attitudes toward using Bitcoin (β = -0.240, p < 0.001).
The analysis indicates that public publicity about Bitcoin is a significant predictor of an individual’s willingness to adopt Bitcoin, H3a is supported (β = 0.101, p < 0.05). Support is found for H3b, which posits that social norms could reinforce individual intention to adopt Bitcoin in the future (β = 0.131, p < 0.001). However, support is not found for H3c, which indicates that social image would significantly reinforce an individual’s willingness to adopt Bitcoin in the future (β = 0.045, non-significant). H3d posits that network effect exerts positive effects on Bitcoin adoption intention (β = 0.478, p < 0.001).

The path coefficient of the relationship between perceived vendor support and intention to use Bitcoin is significant, supporting H4a (β = 0.138, p < 0.01). H4b is supported where evidence found to support that perceived facilitating infrastructure associated with Bitcoin leads to higher intentions to use Bitcoin (β = 0.150, p < 0.001). Support is also found for H5a, which posits that higher self-efficacy will result in a greater willingness to adopt Bitcoin (β = 0.323, p < 0.001). The analysis demonstrates that individuals’ innovativeness positively influences their willingness to use Bitcoin (β = 0.267, p < 0.001), and this positive linkage supports H4b. Moreover, the positive effect of attitude toward using Bitcoin on the intention to use Bitcoin is significant, supporting H6 (β = 0.528, p < 0.001).

Among the demographic characteristics (i.e., age, gender, education level, income, experience), the findings show that education level (β = 0.135, p < 0.01), income (β = 0.76, p < 0.01), and cryptocurrency experience (β = 0.177, p < 0.001) have a significant positive relationship with intention to adopt Bitcoin. Finally, the variables explained 45% of the variance in attitude toward using Bitcoin, and 53% of the variance in willingness to adopt Bitcoin. The R2 scores reflected that the model provides adequate explanatory power to predict the variance in the individual’s attitude toward Bitcoin as well as the intention to adopt Bitcoin in the future.

### Table 3: SEM Results

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Path</th>
<th>Standardized Coefficient</th>
<th>Standard Error</th>
<th>Critical Ratio</th>
<th>Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1a</td>
<td>PA → ATT</td>
<td>0.006</td>
<td>0.05</td>
<td>0.122</td>
<td>Not Supported</td>
</tr>
<tr>
<td>H1b</td>
<td>UNI → ATT</td>
<td>0.043</td>
<td>0.061</td>
<td>0.706</td>
<td>Not Supported</td>
</tr>
<tr>
<td>H1c</td>
<td>INV → ATT</td>
<td>0.656***</td>
<td>0.063</td>
<td>10.414</td>
<td>Supported</td>
</tr>
<tr>
<td>H1d</td>
<td>PEU → ATT</td>
<td>0.165**</td>
<td>0.031</td>
<td>5.329</td>
<td>Supported</td>
</tr>
<tr>
<td>H1e</td>
<td>TT → ATT</td>
<td>0.122**</td>
<td>0.033</td>
<td>3.734</td>
<td>Supported</td>
</tr>
<tr>
<td>H1f</td>
<td>TC → ATT</td>
<td>0.079*</td>
<td>0.032</td>
<td>2.519</td>
<td>Supported</td>
</tr>
<tr>
<td>H2a</td>
<td>PH → ATT</td>
<td>0.163***</td>
<td>0.045</td>
<td>3.638</td>
<td>Supported-Reverse direction</td>
</tr>
<tr>
<td>H2b</td>
<td>VOL → ATT</td>
<td>-0.144*</td>
<td>0.103</td>
<td>-1.105</td>
<td>Supported</td>
</tr>
<tr>
<td>H2c</td>
<td>TR → ATT</td>
<td>-0.098</td>
<td>0.061</td>
<td>-1.607</td>
<td>Not Supported</td>
</tr>
<tr>
<td>H2d</td>
<td>PS → ATT</td>
<td>-0.079**</td>
<td>0.032</td>
<td>-2.519</td>
<td>Supported</td>
</tr>
<tr>
<td>H2e</td>
<td>IRR → ATT</td>
<td>-0.037</td>
<td>0.056</td>
<td>-0.650</td>
<td>Not Supported</td>
</tr>
<tr>
<td>H2f</td>
<td>PTF → ATT</td>
<td>-0.175***</td>
<td>0.038</td>
<td>-4.629</td>
<td>Supported</td>
</tr>
<tr>
<td>H2g</td>
<td>REG → ATT</td>
<td>-0.240***</td>
<td>0.029</td>
<td>-8.389</td>
<td>Supported</td>
</tr>
<tr>
<td>H3a</td>
<td>PP → INT</td>
<td>0.101*</td>
<td>0.026</td>
<td>4.884</td>
<td>Supported</td>
</tr>
<tr>
<td>H3b</td>
<td>SN → INT</td>
<td>0.131***</td>
<td>0.024</td>
<td>5.474</td>
<td>Supported</td>
</tr>
<tr>
<td>H3c</td>
<td>SI → INT</td>
<td>0.045</td>
<td>0.043</td>
<td>1.048</td>
<td>Not Supported</td>
</tr>
<tr>
<td>H3d</td>
<td>NE → INT</td>
<td>0.478***</td>
<td>0.067</td>
<td>7.306</td>
<td>Supported</td>
</tr>
<tr>
<td>H4a</td>
<td>PVS → INT</td>
<td>0.138**</td>
<td>0.041</td>
<td>3.365</td>
<td>Supported</td>
</tr>
<tr>
<td>H4b</td>
<td>PFI → INT</td>
<td>0.150***</td>
<td>0.038</td>
<td>3.966</td>
<td>Supported</td>
</tr>
<tr>
<td>H5a</td>
<td>SE → INT</td>
<td>0.323***</td>
<td>0.033</td>
<td>9.707</td>
<td>Supported</td>
</tr>
<tr>
<td>H5b</td>
<td>INO → INT</td>
<td>0.267***</td>
<td>0.041</td>
<td>6.510</td>
<td>Supported</td>
</tr>
<tr>
<td>H6</td>
<td>ATT → INT</td>
<td>0.528***</td>
<td>0.063</td>
<td>8.380</td>
<td>Supported</td>
</tr>
</tbody>
</table>

Table legend: PA = Perceived Anonymity; UNI= Universality; INV= Investment; PEU= Perceived ease of use; TT= Transaction time; TC= Transaction cost; PH= Physicality; VOL= Volatility; TR= Traceability; PS= Potential scams; IRR= Irreversibility; PTF= Perceived Technical Flaws; REG= Regulation; PP= Perceived publicity; SN= Social norms; SI= Social image; NE= Network effect; PVS= Perceived vendor support; PFI= Perceived facilitating infrastructure; ATT= Attitude toward bitcoin; SE= Self-efficacy; INO = Innovativeness; INT= Intention to use bitcoin.
7. Discussion, Implications, and Conclusion

In this study, we developed and validated Bitcoin adoption conceptualization and survey instrument using a multimethod research design. Although a number of studies have focused on cryptocurrencies such as Bitcoin (Böhme, Christin, Edelman, & Moore, 2015; Kazan, Tan, & Lim, 2015; Li & Wang, 2017), there is no comprehensive model and scales to explain factors affecting individuals to use Bitcoin. Most of the previous studies focus on widely accepted adoption models such as TAM or UTAUT to explain how people decide to adopt (or reject) Bitcoin (Queiroz & Wamba, 2019). Therefore, they mainly articulate adoption intentions based on variables such as ease of use and usefulness of Bitcoin transactions. Studies on digital currencies suggest that usability problems can play a significant role in shaping people’s willingness to adopt Bitcoin (Glomann, Schmid, & Kitajewa, 2019). Moreover, special characteristics of the blockchain (as the underpinning technology behind Bitcoin) may affect the mass adoption of Bitcoin (Hsieh, Vergne, Anderson, Lakhani, & Reitzig, 2018).

This study uses a multimethod research methodology to better explore main drivers and barriers from potential users’ perspectives. Based on a qualitative study (interviews with a focus group, students, and experts) and literature review, we identify five main factors (second-order constructs) predicting individuals’ use behavior of Bitcoin. We then develop a research model to provide insights into the conceptualization of Bitcoin adoption through an empirical study. The model posits that the perceived benefits of Bitcoin can attach more utility to the use of Bitcoin and improve individuals’ attitudes toward adoption and use of Bitcoin in the future. The perceived benefits have a significant effect on the overall perception of utility and attitude because Bitcoin can yield positive utilities through providing investment opportunities, improving the easiness of financial transactions, reducing transaction time and cost. The direct linkage between potential benefits of Bitcoin and attitude toward Bitcoin can encourage prospective users to switch from traditional payment methods to Bitcoin. Consistent with Hughes et al. (2019), the potential benefits associated with the use of Bitcoin are the driving force for individuals to perceive more utility, and, in turn, may increase their willingness to adopt Bitcoin. Our study shows that investment opportunity is the most important driving factor from the perspectives of potential users. This point is consistent with previous studies that stored values of Bitcoin that motivates users to adopt Bitcoin (Lu, Papagiannidis, & Alamanos, 2018).

Moreover, considering potential barriers, many scholars have brought risks to the forefront of cryptocurrency adoption (Raymaekers, 2015). According to the findings of several studies, fraud and security issues have been indicated as the most critical barriers to the widespread adoption of Bitcoin (Böhme et al., 2015). Individuals are concerned about the security of Bitcoin transactions because bitcoin can be vulnerable to fraud, theft, technical flaws, and subversion by skilled computer hackers (Yermack, 2015). Security and regulatory risks associated with Bitcoin may influence individuals’ attitudes and the likelihood that they will use Bitcoin. Our study indicates that regulation issues are the most important barrier for potential users. As Bitcoin is not supported by any official banks and financial institutions, individuals may believe that Bitcoin transactions are not reliable yet. This is in line with previous studies arguing that the blockchain economy needs new governance approaches in terms of transparent decision rights and accountability (Nærland et al., 2017). Thus, the risk perceptions related to the use of Bitcoin can be a significant utility reducer.

Drawing upon utility maximization theory for explaining this trade-off, results show that individuals’ utility function is defined as follows: Utility (X) = Benefit related to use of
Bitcoin- Risk associated with the use of Bitcoin. The benefit is derived from an investment opportunity, digital form of currency, ease of use, transaction time, and cost compared with the traditional exchange options. Risk is a function of high volatility, risk of scams, risk of technical flaws, and lack of regulation. Therefore, findings indicate that the function of positive utility associated with the use of Bitcoin is described as follows: perceived benefit = f (investment, digital form, ease of use, transaction time, and cost). The negative utility function is proposed as follows: perceived risk = f (volatility, scams, technical flaws, unregulated currency). Findings imply that the trade-off between these two functions significantly influences individuals’ attitudes toward the use of Bitcoin.

Our findings also imply that social effects can significantly shape the willingness to use Bitcoin. The rationale behind the inclusion of social effects and facilitating conditions is because even if individuals are aware of possible benefits and risks, they may not necessarily adopt Bitcoin in the present form (Sadhya & Sadhya, 2018). Without a clear picture of social image and beliefs associated with Bitcoin, IT behaviors such as adoption and feature use may be compromised. Consistent with previous studies (Mai et al., 2018), a social image about Bitcoin is developed based on how Bitcoin is discussed in social media, how many people are using Bitcoin, and how Bitcoin is used for different purposes (legal or illegal). According to Hughes et al. (2019), social influences can drive people to adopt Bitcoin. Our study indicates that the network effect is the most important contributor to the social effects. Thus, if potential users believe that many people are using Bitcoin for legal purposes (e.g., online shopping), they become more willing to adopt it in the future.

Our results show that a lack of vendor support and facilitating infrastructures will lead to a lack of user acceptance. As suggested by previous studies, developing the necessary infrastructure is identified as a key predictor of behavioral intention to use Bitcoin (Francisco & Swanson, 2018). Thus, adequate outlets must offer the facility to support Bitcoin payment services. If a majority of businesses and vendors accept Bitcoin, people are more likely to adopt Bitcoin in their day-to-day activities. For instance, facilitating infrastructures such as distributed apps for buying/selling Bitcoin, Bitcoin ATMs, and Bitcoin consulting services should be accessible to potential users to increase the widespread adoption of Bitcoin. This is in agreement with Queiroz and Wamba (2019), suggesting that integration of blockchain technology with vendors’ systems facilitates user adoption.

Finally, we developed two research models: first-order and second-order models. Consistent with prior research, we used the χ2-difference test (Tanriverdi, 2005) and comparative model fit. The results indicate that the model, including the second-order constructs, has a slightly lower χ2 but is statistically significantly different from the first-order model. The second-order model explains 54% of the variance in attitude toward using Bitcoin, and 64% of the variance in willingness to adopt Bitcoin in study 1 and 57% and 63% respectfully in study 2. Moreover, the parsimony in predicting variables that comes with the second-order model caused us to favor this model. Further, all of the fit statistics were better for the second-order model and in the acceptable range (Straub et al., 2004). Thus, we propose that the second-order model formed based on five constructs (i.e., positive utilities, negative utilities, social effects, structural provision, and personal characteristics) is a more parsimonious and statistically significant model with higher explanatory power to predict Bitcoin adoption among non-users.
References


