

# NON-ADOPTION OF CRYPTO-ASSETS: EXPLORING THE ROLE OF TRUST, SELF-EFFICACY, AND RISK

*Research Paper*

Voskoboynikov, Artemij, University of British Columbia, Canada, voskart@ece.ubc.ca

Abramova, Svetlana, University of Innsbruck, Austria, svetlana.abramova@uibk.ac.at

Beznosov, Konstantin, University of British Columbia, Canada, beznosov@ece.ubc.ca

Böhme, Rainer, University of Innsbruck, Austria, rainer.boehme@uibk.ac.at

## **Abstract**

*Over the last years, crypto-assets have gained significant interest from private investors, academia, and industry. While the user population and their motivations, perceptions, and behaviors have been studied, non-adopters and factors influencing their decision have been left unexplored.*

*This work fills this knowledge gap and sheds light on the effects of trust, perceived self-efficacy, and risk, which have been shown to be the key antecedents to technology acceptance, on the adoption intention of non-users. We propose and empirically test a theoretical model that explains the adoption intention of crypto-assets among those, who decided against using them.*

*The validity of the model is assessed in a structural equation model analysis of 204 non-users. Results revealed that trust is a critical factor affecting adoption intention, with perceived self-efficacy having a mediating effect. Building on the results, practical recommendations are offered that could lower the entry barriers and facilitate the adoption of crypto-assets.*

*Keywords: Crypto-assets, cryptocurrencies, technology adoption, adoption intention*

## 1 Introduction

The crypto-asset ecosystem has grown substantially since the introduction of Bitcoin in 2008. In Europe, as of 2018, one in ten owned crypto-assets (ING, 2018) and with ongoing regulatory efforts, such as legislative frameworks that are supposed to reduce the risks for investors (Bitcoin.com, 2020), this number is expected to grow even more. Crypto-assets have also found users in developing countries, such as Nigeria and Kenya, where users adopted them due to their similarity to the already used mobile money (e. g., M-Pesa) (Deutsche Welle, 2020). Despite a substantial body of prior research work investigating the motivations, perceptions, and behaviors of users of bitcoin and other crypto-assets (Abramova and Böhme, 2016; Gao, Clark, and Lindqvist, 2016; Khairuddin et al., 2016; Sas and Khairuddin, 2017; Voskobochnikov et al., 2020), the population of (informed) non-adopters has remained largely unexplored.

To date, motivations and reasons *against* an involvement with crypto-assets have been investigated only qualitatively. Gao, Clark, and Lindqvist (2016) interviewed non-users of bitcoin and found that perceived low self-efficacy associated with the use of bitcoin led to a decision against using it. Similarly, Voskobochnikov et al. (2020) interviewed non-users and found that, besides the low self-efficacy, non-users had little trust in crypto-assets due to the regulatory uncertainty and were concerned about risks associated with the adoption of crypto-assets. While the effect of perceived risk on the usage behavior has been empirically investigated for Bitcoin users (Abramova and Böhme, 2016), its effect as well as the impact of trust and self-efficacy on the adoption intention of non-users have not been studied thus far.

With regard to the above-mentioned constructs, it remains unknown how non-users differ from users. While prior qualitative work has focused on the perceptions of both users and non-users (Gao, Clark, and Lindqvist, 2016; Voskobochnikov et al., 2020), no work comparing these two populations exists. Identifying differences in the key constructs may not only shed light on the previously undocumented reasons against adoption, but might further provide empirical evidence for the importance of certain constructs affecting the actual adoption behaviors, which, to the best of our knowledge, have been ignored in literature.

Information systems (IS) research in related areas, such as Internet (Roy, Kesharwani, and Bisht, 2012; Yousafzai, Pallister, and Foxall, 2005) and mobile banking (Kim, Shin, and Lee, 2009; Lee, Lee, and Kim, 2007; Luo et al., 2010), has shown that all three constructs, i. e., perceived self-efficacy, risk, and trust, are significant predictors of adoption behavior. In these two application areas, however, the technology merely plays a secondary role and only concerns the channel to the bank. This is in stark contrast to crypto-assets, which are unique in a sense that they embody both a financial investment instrument and technology. Crypto-assets are also referred to as a new type of money (Gao, Clark, and Lindqvist, 2016) and while there exist first qualitative studies suggesting the importance of the constructs (Eskandari et al., 2018; Fröhlich, Gutjahr, and Alt, 2020; Gao, Clark, and Lindqvist, 2016; Voskobochnikov et al., 2020) in this domain, there exists no work that empirically investigates the conjectured relations. Understanding these effects can shed light on the underlying barriers to entry and possible ways of addressing them, thereby making the crypto-asset domain more inclusive. This study therefore aims to fill this knowledge gap by answering the following research questions:

R1 *What effect do trust, perceived self-efficacy, and risk have on the adoption intention of informed non-users of crypto-assets?*

R2 *What interaction effects do trust, perceived self-efficacy, and risk have on one another?*

We make several important contributions. Firstly, this study is the first quantitative investigation of crypto-asset non-users and provides empirical evidence of the direct and mediating effects of trust, self-efficacy, and risk on the adoption intention. Secondly, we also provide evidence on the effects of these constructs on the self-reported adoption behavior by combining the user and non-user subsamples. Lastly, based on the results of both analyses, we provide practical recommendations that can be leveraged by practitioners in order to facilitate adoption among non-adopters.

The remainder of the paper is organized as follows. We first provide background on crypto-assets (Section 2) and review related work (Section 3). Next, the theoretical bases of the study are described

(Section 4). Here, trust, perceived self-efficacy, and risk form the foundation of the proposed theoretical model. The methodological approach, including the instrument and sample, as well as the empirical results are presented in Section 5. The paper concludes with a discussion of the results, theoretical, practical, and managerial implications as well as limitations of the study (Section 6).

## 2 Crypto-Assets

Since Bitcoin's introduction in 2008 (Nakamoto, 2008), a plethora of crypto-assets have entered the market. As of November 2020, there exist more than 6 000 different assets worth over USD 450 billion, with new ones emerging on a daily basis (CoinMarketCap, 2020). The use cases of crypto-assets are wide-ranging and go beyond the simple use of a digital currency as envisioned in the original whitepaper (Nakamoto, 2008). Hileman and Rauchs (2017) consider four major categories: *investments*, *medium of exchange*, *payment rail*, and *non-monetary* use cases. The latter became prominent due to emerging platforms that allow to extend the underlying protocol, e. g., of Ethereum (Wood et al., 2014), with executable code. Consequently, various applications were created that resulted in a mainstream appeal (NYTimes, 2017). These extensions are also referred to as digital tokens, which can represent any exchangeable asset, such as collectibles or securities (Crosby et al., 2016). While these tokens provide new capabilities, they share the underlying technology with the platform they were created on. Therefore, we refer to traditional cryptocurrencies, such as bitcoin, and tokens collectively as *crypto-assets* throughout this paper.

Most crypto-assets share the principles of being cryptographically secured and having no centralized governing party (Narayanan et al., 2016). Transactions transfer value from one public key to another and need to be signed, i. e., authorized by using the corresponding private key (Antonopoulos, 2014). These keys define ownership over crypto-assets and are stored in crypto wallets, which can be grouped in custodial and non-custodial. Custodial wallets are third parties that store crypto-assets of many users in an aggregated form, whereas non-custodial wallets assume that the end user is solely responsible for keeping his or her keys secure. Examples of the former are crypto-asset exchanges that are easier to use, but could also lead to monetary losses in case of shutdowns (Moore, Christin, and Szurdi, 2018). While non-custodial wallets are known to be less user-friendly (Eskandari et al., 2018; Fröhlich, Gutjahr, and Alt, 2020; Voskoboynikov et al., 2020), they guarantee that no one other than the user can access the funds.

## 3 Literature Review

There exists an extensive body of research investigating the factors that influence the adoption of information technology. Arguably, the most popular model is the Technology Acceptance Model (TAM) (Davis, 1989), which incorporates *perceived ease of use* and *perceived usefulness* as two constructs that influence an individual's decision to adopt and use a new technology. This model and its extensions, such as the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh and Davis, 2000), have been successfully applied in various IS domains, including, but not limited to, the fintech sector (e. g., Hanafizadeh et al., 2014; Kim and Kim, 2005; Lai and Li, 2005; Pikkarainen et al., 2004). They have been shown to explain a significant proportion of the variance in the dependent variable, i. e., the behavioral intention to adopt the respective technology or software.

Since crypto-assets can be used as a digital currency, this study is guided by prior work on electronic payment systems. Hanafizadeh, Keating, and Khedmatgozar (2014) conducted a review of 165 studies between 1999 and 2012 that explored the factors influencing the adoption of Internet banking. They found that the vast majority of theory-driven publications employed the TAM or its extensions. The latter often included cultural or study-specific variables, but also constructs, such as *risk* and *trust*, that were shown to play a vital role. The first evidence of their significance was provided by Pavlou (2003) and Gefen, Karahanna, and Straub (2003) in the context of e-commerce, and was later confirmed for mobile banking (e. g., Akturan and Tezcan, 2012; Kim, Shin, and Lee, 2009; Lee, Lee, and Kim, 2007; Luo et al., 2010). For example, Lee et al. (2007) conducted a survey with 306 participants and studied the effect of risk

and trust perceptions on the adoption of mobile banking in Korea. Both constructs comprised multiple dimensions, with trust being a significant predictor of the adoption.

Similarly, Luo et al. (2010) investigated the effects of risk and trust on mobile banking adoption. Contrary to Lee et al. (2007), however, the authors included more dimensions in their constructs and further investigated the interactions between them. Both constructs were found to be significant predictors, with risk having a negative and trust a positive effect on the behavioral intention.

More recent studies have also confirmed the importance of trust in adoption behaviors (e. g., Alalwan, Dwivedi, and Rana, 2017; Sharma and Sharma, 2019). Both Alalwan et al. (2017) and Sharma and Sharma (2019) extended the UTAUT2 and information systems success models (Delone and McLean, 2003) respectively by including trust dimensions, and provided empirical evidence for the hypothesized effects. Another prominent construct influencing adoption behavior is *perceived self-efficacy* (Alalwan et al., 2015; Jeong, Yoon, et al., 2013; Luarn and Lin, 2005; Marakarkandy, Yajnik, and Dasgupta, 2017; Mun and Hwang, 2003; Zhou, 2012). It refers to an individual's perceived capabilities to achieve designated levels of performance in a given context (Bandura (2010)). Its importance has been confirmed by scholars for mobile banking, both for users (Luarn and Lin, 2005; Zhou, 2012) and non-users (Jeong, Yoon, et al., 2013). Whereas Zhou (2012) considered the moderating effect of self-efficacy on the initial trust of mobile users, Luarn et al. (2005) investigated the direct effects of self-efficacy on the behavioral intention. Among commonly included constructs in the TAM, self-efficacy was found to have a positive effect on the intention to use mobile banking services. Likewise, self-efficacy appears to have an impact on non-users. Jeong and Yoon (2013) investigated the adoption behaviors of both users and non-users of mobile banking and identified self-efficacy as a significant predictor of adoption for non-users.

There exists an extensive body of empirical research on crypto-asset users (see Table 1). Their motivations, perceptions, and behaviors have been investigated in both qualitative and quantitative studies. However, contrary to the extensive research body on mobile banking, studies uncovering the reasons for or against the use of crypto-assets are scarce. This also holds true for the population of non-users, which has been largely ignored. Prior work suggests that both the perceived low self-efficacy Gao, Clark, and Lindqvist, 2016 and lack of institutional trust Voskobochnikov et al., 2020 are adoption inhibitors, however, neither effect has been validated quantitatively yet and this study aims to fill this knowledge gap.

| Year | Qualitative studies   | Quantitative studies                                 |
|------|---|--|
| 2020 | Mai et al. (2020)<br>Fröhlich et al. (2020)<br>Voskobochnikov et al. (2020) |  |
| 2019 | Khairuddin and Sas (2019)   | Arias-Oliva et al. (2019)<br>Stix et al. (2019) *    |
| 2018 |   | Rauchs et al. (2018)<br>Henry et al. (2018) *        |
| 2017 | Sas and Khairuddin (2017)   | Rauchs et al. (2017)                                 |
| 2016 | Gao et al. (2016)<br>Khairuddin and Sas (2016)                              | Krombholz et al. (2016)<br>Abramova and Böhme (2016) |
| 2015 | Baur et al. (2015)  |  |
| 2014 |   | Bohr and Bashir (2014) **                            |

\* Representative nationwide sample

\*\* Use of secondary data collected on related Bitcoin sites

Table 1: Overview of empirical studies on crypto-assets

## 4 Research Model

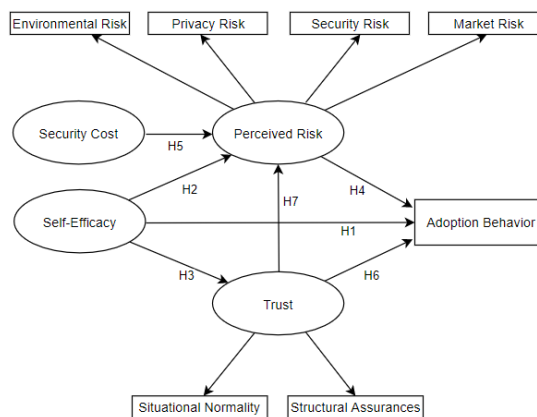


Figure 1: Research model

The following sections contextualize the theoretical constructs of perceived self-efficacy, trust, and risk, and reference relevant studies that show interactions between them. The hypotheses, shown in Figure 1, are based on prior findings in the fintech domain and qualitative studies of the populations of crypto-asset users and non-users. All items in the questionnaire were a stimulus to a non-observable latent variable and were therefore modeled as reflective.

### 4.1 Self-Efficacy

The effect of self-efficacy is well-documented in the fintech domain, both for online (Alalwan et al., 2015; Marakarkandy, Yajnik, and Dasgupta, 2017) and mobile banking (Jeong, Yoon, et al., 2013; Luarn and Lin, 2005; Zhou, 2012). Exploratory qualitative studies have investigated its effect on both users and non-users of bitcoin and other crypto-assets. Gao et al. (2016) found that non-users believed to lack required skills that would enable them to use bitcoin and cited this as their main argument against an involvement. Voskoboynikov et al. (2020) expanded the object of the study beyond bitcoin and interviewed users and non-users of crypto-assets in general. Their findings confirm non-users' perceived low self-efficacy towards crypto-assets and the respective tools. Users in both studies, on the other hand, were familiar with the ecosystem, knew the tools, and believed to understand the underlying technology well-enough to be comfortable to use it. These findings lead to our first hypothesis:

**H1:** The perceived self-efficacy has a positive effect on the non-users' intention to adopt crypto-assets.

Perceived self-efficacy was also shown to have an effect on both risk and trust. In the study of consumers' purchase intentions in e-commerce (Kim and Kim, 2005), the authors found that self-efficacy had a significant positive effect on trust, while also reducing the perceived risk. Zhou (2012) confirmed the positive effect of self-efficacy on the initial trust formation for users of mobile banking as well.

In the context of crypto-assets, the interactions between these constructs were not investigated so far. Following the empirical results in related domains, we believe that similar effects might exist in the crypto-asset context:

**H2:** The perceived self-efficacy has a negative effect on the non-users' perceived risk associated with crypto-assets.

**H3:** The perceived self-efficacy has a positive effect on non-users' trust towards crypto-assets.

## 4.2 Perceived Risk

Perceived risk negatively affects users' intention to engage in online transactions. Its negative effect has been shown for e-commerce (Chiu et al., 2014; Kim and Kim, 2005; Riek, Abramova, and Böhme, 2017), Internet (Martins, Oliveira, and Popovič, 2014; Roy, Kesharwani, and Bisht, 2012) and mobile banking (Akturan and Tezcan, 2012; Lee, Lee, and Kim, 2007; Luo et al., 2010; Makanyeza, 2017). These findings imply that consumers with high risk concerns are less likely to adopt the respective technology.

Overall, there exists a substantial number of risks that are associated with crypto-assets. Besides the possible attack vectors compromising the distributed ledger (Bonneau et al., 2015), self-errors (Sas and Khairuddin, 2017; Voskobochnikov et al., 2020) and shutdowns of third-party services (Moore, Christin, and Szurdi, 2018) such as exchanges are known to be prevalent and could lead to irreversible monetary losses. These and other risks have been documented in the crypto-asset literature (Böhme et al., 2015; Grant and Hogan, 2015; Kiran and Stanett, 2015), with Kiran and Stanett (2015) suggesting a grouping into *social, legal, economic, technological, and security risks*.

Abramova and Böhme (2016) were the first to shed light on the effect of the perceived risk on the behavior of bitcoin users. In their study, risk was considered as a multi-faceted construct, and included the legal, operational, adoption, and financial risks. The authors found that the perceived risk was a strongly significant indicator that negatively influenced the participants' willingness to transact with Bitcoin.

The effect of risk on non-users has been only the object of qualitative studies thus far. Non-users were concerned about security vulnerabilities of crypto-assets, exchanges, tools, legal uncertainty, as well as privacy (Voskobochnikov et al., 2020). Another prevalent theme was the negative stigma surrounding crypto-assets. Non-users believed that crypto-assets were exploited for illicit activities, such as the drug trade, and viewed an involvement unsafe as they preferred not to be associated with such behaviors.

Similar to Abramova and Böhme (2016), we consider the *perceived risk* as one's perception of the uncertainty and negative consequences associated with the adoption of crypto-assets, albeit from a non-user's perspective. Based on prior findings for both mobile banking (Luo et al., 2010) and crypto-assets (Abramova and Böhme, 2016; Voskobochnikov et al., 2020), we hypothesize the following:

**H4:** The perceived risk associated with crypto-assets negatively affects non-users' adoption intention.

## 4.3 Security Cost

Prior qualitative studies have shown that both users and non-users of crypto-assets often find security practices complicated (Fröhlich, Gutjahr, and Alt, 2020; Voskobochnikov et al., 2020). Fröhlich et al. (2020) found that users were bothered by the secure key management and believed that a certain knowledge level is required in order to be able to successfully manage private keys. Similar findings were reported for non-users by Voskobochnikov et al. (2020), who identified struggles of non-users related to keeping track of secure and trustworthy tools. Perceived security cost is closely related to the perceived security efficacy which captures an individual's belief in their ability to protect a system from threats or attacks (Nguyen and Kim, 2017). Prior work has shown its effect on the risk perception of information system users. Nguyen and Kim (2017) found a strongly significant negative effect of security efficacy on the perceived risk. Jansen (2015) report similar findings for Internet banking, where the associated efficacy was found to have a negative effect on the perceived risk.

For non-users of crypto-assets, however, the associated cost of security measures is likely to have an opposite effect. Based on findings of prior interview studies (Fröhlich, Gutjahr, and Alt, 2020; Voskobochnikov et al., 2020), non-users will likely perceive security measures as costly due to a lower perceived security efficacy. We believe that this assessment would lead to an increase in the perceived risk:

**H5:** The perceived cost of securing crypto-assets has a positive effect on the non-users' perceived risk.

## 4.4 Trust

Trust was shown to be a significant predictor of technology adoption. Its positive effect for the adoption of mobile banking is well-documented (Kim, Shin, and Lee, 2009; Lee, Lee, and Kim, 2007; Luo et al., 2010). However, the interactions between trust, its dimensions and the adoption behavior in the context of crypto-assets are largely unexplored. Sas et al. (2017) interviewed 20 bitcoin users and investigated the trust determinants in three dimensions: technological, social, and institutional. One of the major findings was that due to the unregulated and pseudonymous nature of Bitcoin, the institutional trust was limited and posed a risk to the users. Voskobojnikov et al. (2020) identified regulatory concerns as one of the major concerns of non-users that led to a decision against using crypto-assets. Based on these findings, we investigate the effect of institutional trust on the intention to adopt crypto-assets. While other dimensions of trust can be found in literature (Liu, Min, and Ji, 2009; Tan and Sutherland, 2004), we take a pragmatic perspective and focus on institutional trust, as there exists first empirical evidence for its effect on non-adopters (Voskobojnikov et al., 2020).

Since institutional trust is multi-faceted, we consider its several dimensions. According to Gefen et al. (2003), there exist two institution-based first-order constructs: *situational normality*, i. e., the perceived normality of a situation or a transaction in the context of crypto-assets, as well as *structural assurances*, i. e., existing safety nets that include guarantees and regulations. Yousafzai et al. (2005) found that both structural assurances and situational normality increased the participants' trust beliefs in online banks. Similar findings were also confirmed for mobile banking by Gu et al. (2009), who found that both constructs significantly increased the perceived trust among users. Following these insights, we consider both constructs in our study and believe that those non-users who score higher on the latent construct of institutional trust are more likely to adopt crypto-assets.

**H6:** Trust in crypto-assets will positively affect non-users' intention to adopt them.

Trust also has an effect on risk, as both are closely related. Das et al. (2004) further suggest that both are mirror images of each other. Several scholars have investigated the effect of trust on risk and observed a negative effect. This has been shown for both e-commerce (Kim and Kim, 2005) and mobile banking (Kim, Shin, and Lee, 2009; Lee, Lee, and Kim, 2007; Luo et al., 2010). For example, Luo et al. (2010) showed that structural assurance has a negative effect on risk in mobile banking, implying that the belief in the institutional environment's safety leads to a reduction in the perceived risk. Thus, we hypothesize:

**H7:** Trust in crypto-assets will negatively affect the non-users' perceived risk associated with them.

## 5 Research Methodology and Results

### 5.1 Instrument Design and Data Collection

An online survey was conducted in order to examine and test the proposed research model. The primary research objective of this work was to investigate non-users' perceptions and the factors influencing their decision not to adopt crypto-assets. Non-users did not own any crypto-assets at the point of the survey, however, had an understanding of the domain, which was a self-reported option "*No, I have never held [crypto-assets] but have some domain knowledge.*"

However, we were also interested in comparing perceptions of non-adopters with those of actual users of crypto-assets. For this reason, we decided to further recruit current users. After conducting a pilot with 30 participants, both users ( $N = 200$ ) and non-users ( $N = 204$ ) were recruited through the commercial service provided by Qualtrics.<sup>1</sup> Crypto-asset ownership was predetermined by Qualtrics and both participant groups were recruited in June 2020 after the study was approved by the ethical boards of the involved institution. All participants resided in the U.S. and were over the age of 18.

<sup>1</sup> Qualtrics Panel: <https://www.qualtrics.com/research-services/online-sample/>

| Characteristic                          | Users      | Non-Users  |
|---|------------|------------|
| <i>N</i>                                | 200 (100%) | 204 (100%) |
| <b>Gender</b>                           |            |            |
| Male                                    | 75.5%      | 37.3%      |
| Female                                  | 24.5%      | 62.3%      |
| <b>Age</b>                              |            |            |
| 18–24                                   | 11.5%      | 19.1%      |
| 25–34 years                             | 26.5%      | 18.6%      |
| 35–44 years                             | 46.5%      | 15.7%      |
| 45–54 years                             | 13.0%      | 12.7%      |
| 55–64 years                             | 2.5%       | 16.7%      |
| 65+                                     | 0.0%       | 17.2%      |
| <b>Education</b>                        |            |            |
| High school graduate (or an equivalent) | 9.0%       | 25.0%      |
| College or associate degree             | 9.0%       | 20.1%      |
| Bachelor's degree                       | 27.5%      | 33.3%      |
| Master's degree                         | 37.5%      | 14.7%      |
| Doctorate degree                        | 13.0%      | 2.9%       |
| Other                                   | 4.0%       | 4.0%       |

Table 2: Subsample demographics

## 5.2 Measurement Model

The main objective of this study is the investigation of the adoption behaviors of crypto-asset non-users, with the dependent variable being operationalized as one's intention to purchase crypto-assets in 2020 (see *Adoption Intention* in Table 5). Here, a three-item nominal scale was used (“Yes”, “No”, “I don't know”). However, as we also intended to compare non-users with current users of crypto-assets, we further tested a modified version of the model, in which the dependent binary variable is coded as the self-reported *Adoption Behavior*, i. e., whether an individual did or did not own crypto-assets at the time of the survey. The model of *Adoption Intention* depicted in Figure 1 is tested on data collected from the 204 non-users, whereas *Adoption Behavior* was analyzed using data from the combined sample of 404 participants.

Both models have the same risk construct, which, similar to prior work (Abramova and Böhme, 2016; Luo et al., 2010), is modeled as multi-dimensional. As our study is the first quantitative investigation of risk perceptions of non-users of crypto-assets, we included a wide range of risks in the survey and performed a separate exploratory factor analysis (with Varimax rotation) to identify the risk items that load together. For all risks, respondents were asked to rate the level of their concern on a five-point Likert scale.

Drawing upon the analysis, we differentiate between the four first-order constructs in our model: (1) *Environmental Risk (ER)* captures both regulatory and adoption uncertainty; (2) *Privacy Risk (PR)* captures the possibility of transactions being linked by parties to the individual user; (3) *Market Risk (MR)* reflects the possibility of experiencing losses due to the volatility of market prices; (4) *Security Risk (SR)* refers to potential security vulnerabilities in tools that could lead to losses. We excluded risk items that did not load sufficiently on the first four components and considered only factor loadings that were 0.6 or higher. This cutoff is above the recommended 0.5 (Hair et al., 1998) and was used in the context of Bitcoin as well (Abramova and Böhme, 2016).

We assessed the measurement model by evaluating its internal consistency as well as convergent and discriminant validity. The composite reliability (CR) indicator was used to evaluate the internal consistency. As evident in Table 3, two of our latent risk items are marginally below the suggested threshold of 0.6 for exploratory research (Hair et al., 1998). One possible explanation is that we formed the risk constructs strictly based on the results of the exploratory factor analysis. Some risks, e. g., MR2, were phrased very broadly and could be interpreted differently by an individual respondent. However, based on the CR values of 0.58 for SR and 0.56 for MR respectively, we believe that the CR values are close enough for the constructs to be incorporated in our model.

Convergent validity was evaluated by assessing the factor loadings and the average variance extracted (AVE) (Fornell and Larcker, 1981). The factor loadings for all indicators are above the recommended



threshold of 0.5 (Hair et al., 1998). The suggested threshold for AVE is 0.5 (Fornell and Larcker, 1981) and all constructs except for *MR* and *ER* are above this value. According to Fornell and Larcker (1981), the convergent validity of items with an AVE lower than 0.5 and a CR higher than 0.6 are still considered adequate. Therefore, only *MR* is under the suggested threshold. The research model with *Adoption Behavior* as the dependent variable also satisfied the criteria for all constructs but *MR*.

| Item | Loading | Construct | CR   | Mean | AVE  | Item | Loading | Construct | CR   | Mean | AVE  |
|------|---------|-----------|------|------|------|------|---------|-----------|------|------|------|
| SE1  | 0.82    | SE        | 0.87 | 2.41 | 0.68 | ER1  | 0.72    | ER        | 0.75 | 3.51 | 0.47 |
| SE2  | 0.83    |           |      |      |      | ER2  | 0.68    |           |      |      |      |
| SE3  | 0.80    |           |      |      |      | ER3  | 0.62    |           |      |      |      |
| SE4  | 0.85    |           |      |      |      | ER4  | 0.74    |           |      |      |      |
| SC1  | 0.78    | SC        | 0.81 | 3.40 | 0.66 | PR1  | 0.73    | PR        | 0.79 | 3.33 | 0.61 |
| SC2  | 0.88    |           |      |      |      | PR2  | 0.81    |           |      |      |      |
| SC3  | 0.78    |           |      |      |      | PR3  | 0.80    |           |      |      |      |
| SN1  | 0.93    | SN        | 0.77 | 2.51 | 0.70 | MR1  | 0.72    | MR        | 0.57 | 3.81 | 0.45 |
| SN2  | 0.74    |           |      |      |      | MR2  | 0.61    |           |      |      |      |
| SA1  | 0.86    | SA        | 0.88 | 2.70 | 0.78 | SR1  | 0.65    | SR        | 0.58 | 3.74 | 0.58 |
| SA2  | 0.92    |           |      |      |      | SR2  | 0.81    |           |      |      |      |
| SA3  | 0.87    |           |      |      |      | SR3  | 0.82    |           |      |      |      |

Table 3: Reliability measures of first-order latent constructs

Lastly, we evaluated the discriminant validity of our research model. The Fornell-Larcker criterion is commonly used in literature and suggests that the square root of AVE of each construct should be greater than any of the bi-variate correlations involving the construct (Hair et al., 1998). Table 4 shows that this criterion is met for all constructs, but *MR*, *ER*, and *SN*. The high correlation among *SN* and *SA* is expected as both are measuring the institutional dimension of trust. We further applied the Heterotrait-Monotrait Ratio of Correlations (HTMT) criterion (Henseler, Ringle, and Sarstedt, 2015) and all our constructs were under the recommended value of 0.9. The model with *Adoption Behavior* as dependent variable satisfied this criterion for all constructs but the pair of *SN-SA*, where the score was marginally over 0.9. Overall, however, we believe that the discriminant validity is acceptable for both models.

|    | SE          | SC          | SN          | SA          | ER          | PR          | SR          | MR          |
|----|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|
| SE | <b>0.83</b> |             |             |             |             |             |             |             |
| SC | -0.06       | <b>0.81</b> |             |             |             |             |             |             |
| SN | 0.70        | 0.02        | <b>0.84</b> |             |             |             |             |             |
| SA | 0.75        | -0.14       | 0.85        | <b>0.88</b> |             |             |             |             |
| ER | -0.41       | 0.29        | -0.31       | -0.39       | <b>0.69</b> |             |             |             |
| PR | -0.05       | 0.29        | 0.06        | -0.05       | 0.44        | <b>0.78</b> |             |             |
| SR | -0.44       | 0.37        | -0.34       | -0.47       | 0.72        | 0.44        | <b>0.67</b> |             |
| MR | -0.39       | 0.43        | -0.29       | -0.45       | 0.67        | 0.26        | 0.70        | <b>0.76</b> |

Table 4: Fornell-Larcker criterion analysis

We also compared the constructs between both samples in order to investigate statistical differences. The means of the indicators were compared using a two-sample t-test and the results can be found in Table 5. The results of the two-sample t-tests suggest that there are significant differences between the two subsamples. Users have higher perceived *Self-Efficacy* with the differences for all four indicators being strongly significant. Similar results can also be observed for the two trust constructs. With regard to the risks, only the differences for the indicators of the *Security Risk* construct are significant. We also questioned non-users about their specific reasons against the adoption of crypto-assets with the possibility to choose multiple options. Table 6 illustrates the responses in descending order.

| Question   | Item | Users |      | Non-Users |      | p    |
|--|------|-------|------|-----------|------|------|
|  |      | Mean  | SD   | Mean      | SD   |      |
| How confident are you in the following skill areas in the context of crypto-assets?                |      |       |      |           |      |      |
| Purchasing crypto-assets.  | SE1  | 3.88  | 1.11 | 2.51      | 1.16 | ***  |
| Making payments with crypto-assets.  | SE2  | 3.90  | 1.01 | 2.42      | 1.20 | ***  |
| Explaining the difference between the private and public key.                                      | SE3  | 3.68  | 1.10 | 2.22      | 1.20 | ***  |
| Explaining the purpose of transaction fees.  | SE4  | 3.83  | 1.01 | 2.50      | 1.19 | ***  |
| Please indicate how costly are the following measures in terms of required time and money.         |      |       |      |           |      |      |
| Securing crypto-assets   | SC1  | 3.40  | 1.17 | 3.37      | 0.94 | n.s. |
| Keeping security measures for crypto-assets up-to-date   | SC2  | 3.48  | 1.08 | 3.47      | 0.99 | n.s. |
| Security investments into equipment  | SC3  | 3.58  | 1.05 | 3.51      | 0.99 | n.s. |
| Please indicate to what extent do you agree with the following statements.                         |      |       |      |           |      |      |
| I feel confident that the technological features of crypto-assets make it safe for me to use them. | SA1  | 3.87  | 1.10 | 2.73      | 1.06 | ***  |
| I feel that existing safeguards adequately protect me when using crypto-asset exchanges.           | SA2  | 3.88  | 0.97 | 2.67      | 1.11 | ***  |
| In general, the environment in which I can use crypto-assets is robust and safe.                   | SA3  | 3.84  | 1.06 | 2.71      | 1.13 | ***  |
| Please indicate to what extent do you agree with the following statements.                         |      |       |      |           |      |      |
| I feel that most crypto-asset exchanges act in their customers' best interest.                     | SN1  | 3.87  | 1.05 | 2.72      | 1.06 | ***  |
| I feel that most merchants who accept crypto-assets act in their customers' best interest.         | SN2  | 3.63  | 1.09 | 2.92      | 1.14 | ***  |
| To what extent are you concerned about the following risks related to crypto-assets?               |      |       |      |           |      |      |
| I am concerned about   |      |       |      |           |      |      |
| the legal uncertainty for the users of crypto-assets and possible prosecution                      | ER1  | 3.38  | 1.15 | 3.66      | 1.11 | *    |
| the restricted crypto-asset usage because of regulatory involvement                                | ER2  | 3.43  | 1.08 | 3.39      | 0.99 | n.s. |
| the lack of wide adoption of crypto-assets   | ER3  | 3.50  | 1.14 | 3.51      | 1.12 | n.s. |
| the lack of interoperability of crypto-assets with other services                                  | ER4  | 3.42  | 1.08 | 3.50      | 1.05 | n.s. |
| the traceability of transactions by governments  | PR1  | 3.29  | 1.17 | 3.20      | 1.08 | n.s. |
| the traceability of transactions by firms/private sector   | PR2  | 3.33  | 1.16 | 3.30      | 1.11 | n.s. |
| the traceability of transactions by individuals  | PR3  | 3.42  | 1.14 | 3.38      | 1.18 | n.s. |
| the theft of private keys  | SR1  | 3.40  | 1.15 | 3.73      | 0.99 | **   |
| security vulnerabilities of wallets  | SR2  | 3.52  | 1.10 | 3.73      | 0.96 | *    |
| security vulnerabilities of exchanges  | SR3  | 3.5   | 1.11 | 3.77      | 1.02 | *    |
| the volatility of the market price   | MR1  | 3.76  | 1.01 | 3.79      | 1.01 | n.s. |
| I agree that the users of crypto-assets are risk-takers.   | MR2  | 3.62  | 1.05 | 3.82      | 0.95 | *    |
| Are you considering purchasing crypto-assets in 2020?  | AI   |       |      |           |      |      |

Table 5: Results of two-sample t-tests between users and non-users

| Item   | Frequency | Item  | Frequency |
|--|-----------|---|-----------|
| Concern of falling victim to fraud or crime                | 95        | Lack of regulatory support  | 62        |
| Fear of possible security vulnerabilities in crypto-assets | 85        | Lack of incentives or use cases   | 42        |
| Fear of possible security vulnerabilities in wallets       | 78        | Negative stigma associated with crypto-assets                           | 31        |
| Volatile nature of crypto-assets                           | 69        | Negative experience with service providers, e. g., exchanges or wallets | 17        |

Table 6: Reported reasons against using crypto-assets

### 5.3 Structural Model

To validate the theoretical models, structural equation models (SEM) were built using the lavaan (latent variable analysis) package (Rosseel, 2012) for the programming language R (version 4.0). The results of the analysis suggest that our models explain 25% of the variance in *Adoption Intention* and 62% of the variance in *Adoption Behavior*, respectively.

The fit of the structural models can be assessed by using a combination of fit measures. Following the suggestion of Kline (2015), we report the ratio of the Chi-square value to the degrees of freedom ( $\chi^2/df$ ), Comparative Fit Index (CFI), Standardized Root Mean Square Residual (SRMR), and Root Mean Square Error of Approximation (RMSEA). Hu and Bentler (1999) suggest that a model is considered a good fit if the CFI is close to 0.95, SRMR – to 0.08, and RMSEA – to 0.06. There exists no consensus with regards to  $\chi^2/df$ , where some suggest a value of less than 5 (Marsh and Hocevar, 1985) and others considering a value between 2 and 3 as acceptable (McIver and Carmines, 1981). As reported in Figure 2, both our models satisfy these conditions and therefore have a reasonably good fit to the data.

The results of the structural equation model with *Adoption Intention* as the dependent variable (see Figure 2a) suggest that several of our hypotheses are supported. *Trust* is the only construct that has a

significant positive effect on *Adoption Intention* ( $\beta = 0.39, p < 0.05$ ). Against our expectations, both *Perceived Risk* and *Self-Efficacy* have no significant effect on *Adoption Intention*. However, *Trust* acts as a mediator in the model: if the construct is removed, the positive effect of *Self-Efficacy* on *Adoption Intention* becomes strongly significant ( $\beta = 0.49, p < 0.001$ ). *Self-Efficacy* has a significant positive effect on *Trust* ( $\beta = 0.77, p < 0.001$ ), and *Trust* has a significant negative effect on *Perceived Risk* ( $\beta = -0.25, p < 0.05$ ). Lastly, *Security Cost* is found to have a strongly significant positive effect on *Perceived Risk* ( $\beta = 0.40, p < 0.001$ ). For the second structural model (Figure 2b), only the positive effect of *Self-Efficacy* on *Adoption Behavior* is significant ( $\beta = 0.75, p < 0.001$ ). *Self-Efficacy* further has a significant positive effect on *Trust* ( $\beta = 0.90, p < 0.001$ ), whereas *Security Cost* has a significant positive effect on *Perceived Risk* ( $\beta = 0.44, p < 0.001$ ).

We validated the results by running the analysis using PLS-SEM (SmartPLS). Both approaches produced comparable results, with PLS-SEM even identifying a significant effect of trust on adoption behavior, which is not the case for CB-SEM (see Figure 2b). Since CB-SEM is known as a more rigorous and strict test (Astrachan, Patel, and Wanzenried, 2014), the reported results and conclusions are therefore more conservative.

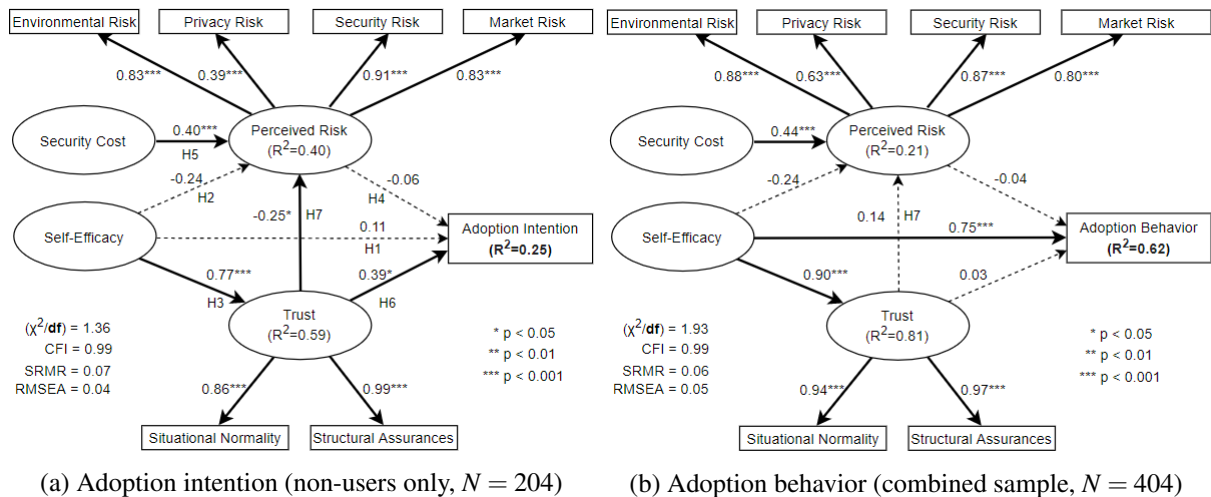


Figure 2: Result of the structural equation models

## 6 Discussion

### 6.1 Theoretical Implications

There only exists limited work that investigated interactions between the examined theoretical constructs in the context of crypto-assets. Abramova and Böhme (2016) found that perceived benefit and perceived ease of use had a positive effect on usage behavior, while perceived risk had a negative effect. Arias-Oliva et al. (2019) found the performance expectancy and facilitating conditions to be significant predictors of behavioral intention. Based on the findings of prior work, the theoretical model in this study sheds light on the effects of trust, self-efficacy, and risk on the non-user's intention to adopt crypto-assets.

Thus far, non-users of crypto-assets have only been the subject of qualitative studies. Against this backdrop, our work provides the first empirical analysis of the factors influencing the adoption intention. Contrary to our original expectations, only *Trust* has a direct significant effect on *Adoption Intention*. Therefore, we are not able to confirm prior qualitative findings that suggest an effect of risk and self-efficacy (Gao, Clark, and Lindqvist, 2016; Voskoboynikov et al., 2020). Yet, interestingly, *Self-Efficacy* has an indirect effect on *Adoption Intention*, suggesting that those participants who have higher perceived self-efficacy also score higher on the trust construct and hence, are more likely to adopt crypto-assets.

The importance of *Self-Efficacy* is even more evident in the second model (Figure 2b), where *Self-Efficacy* has a strongly significant effect on *Adoption Behavior*. A reason for the different observations could be that non-users have difficulties in assessing their self-efficacy accurately, particularly if they only have limited knowledge. In this case, institutional trust acts as a full mediator.

We cannot confirm the negative effect of *Perceived Risk* on neither *Adoption Intention* nor *Adoption Behavior*. This finding is in stark contrast to prior work on crypto-assets (e.g., Sas and Khairuddin, 2017; Voskobochnikov et al., 2020) and also other domains, such as mobile banking (e.g., Luo et al., 2010), where perceived risk was found to have a negative effect on the adoption behaviors. This is corroborated through the comparison of the first order risk constructs which did not yield a consistent picture. It appears that other constructs play a more vital role in technology adoption among informed non-adopters, such as *Self-Efficacy*, *Situational Normality*, and *Structural Assurances*, where the user subsample in our study scored significantly higher. These insights were only made possible through the investigation of both the user and non-user subsamples and we therefore believe that in order to understand the intricacies of technology adoption, one needs to go beyond the intention to adopt as it only provides a partial picture. With regard to the different risks in the crypto-asset domain, *Security Risk* has the highest path coefficient. This matches the self-reported reasons of non-users for which they decided against adoption. The three most frequent reasons were all related to either falling victim to crime or software vulnerabilities (see Table 6), followed by the lack of regulatory support or the volatile nature, which are commonly reported in prior work (Presthus and O'Malley, 2017; Walton and Johnston, 2018). Overall, we conjecture that both users and informed non-users are aware of the most common risks, which explains the insignificant effect on both adoption intention and behavior. This is plausible as the adoption of crypto-assets itself does not pose any direct personal harm or financial loss on individuals, as opposed to the actual usage, which has been shown to be affected negatively by risk (Abramova and Böhme, 2016).

We also confirm the effects of *Trust* and *Security Cost* on *Perceived Risk* in the context of crypto-assets. Trust can therefore act as an important factor that can be leveraged to reduce the overall perceived risk. Lastly, *Security Cost* is also found to be a strongly significant predictor of *Perceived Risk*. This is not surprising, as poor user experience (UX) of crypto-asset tools, such as exchanges and wallets, is well-known and reported in literature (Fröhlich, Gutjahr, and Alt, 2020; Sas and Khairuddin, 2017).

Crypto-asset users, however, are not necessarily confronted with those UX challenges. This is particularly true in the case of crypto-asset exchanges, which provide an abstraction layer and allow users to own crypto-assets without having to deal with the private key management and therefore the actual technology. Crypto-assets therefore show the limits of the traditional understanding of technology adoption as it is unclear whether one can truly speak of adoption in cases in which users are merely interacting on an abstraction layer and not with the technology itself. More work is needed in order to operationalize technology adoption in the context of crypto-assets.

## 6.2 Practical Implications

This study has several important implications for actors in the crypto-asset domain, such as regulators, blockchain start-ups, and tool developers. *Trust* was the only significant direct predictor of *Adoption Intention*, suggesting that participants who have more trust in the ecosystem surrounding crypto-assets are more likely to adopt them. Improving both the *Situational Normality* and *Structural Assurances* could therefore have a positive effect on a participant's willingness to adopt crypto-assets. Situational normality is the degree to which a situation appears normal or customary (Gefen, Karahanna, and Straub, 2003). Following our results, providers of crypto-asset services should try mimicking online banking or conventional payment systems that non-users are already familiar with. Attaining situational normality could also be achieved by introducing stable crypto-assets, so-called stable coins, to non-users, which, in turn, increase their trust due to the similarities to fiat currencies. Trust, however, could also be increased by providing more structural assurances that would protect potential newcomers. Regulatory uncertainty is often associated with crypto-assets and attracts malicious actors, such as exchanges that

might disappear with users' funds (Moore, Christin, and Szurdi, 2018) or fraudulent Initial Coin Offerings (ICOs) (CoinTelegraph, 2020). Non-users feel unsafe in such environment and need additional signals of trust. In e-commerce, trustworthiness is often signaled through trust badges, which could be introduced for operators of exchanges in this domain. These badges, however, have to be costly or hard to fake in order to avoid exploits by fraudulent parties (Riegelsberger, Sasse, and McCarthy, 2005). Alternatively, similar to traditional banking, deposit insurances (e. g., by the Federal Deposit Insurance Corporation) could provide safety nets in the case of exchanges. However, crypto-asset deposits, contrary to the US dollar, are not yet insured, which calls for further regulatory involvement in order to facilitate adoption. The results of the structural models have shown that *Self-Efficacy* has a significant positive effect on *Trust* and *Adoption Behavior*. Managerial attention should be therefore focused on the attainment of self-efficacy, which could be achieved in various ways. For example, training sessions could be used to let newcomers familiarize themselves with the terminology and technology prior to an actual engagement. Better tool support could also increase self-efficacy among non-users. Prior work has identified challenges of crypto-asset tools, including, but not limited to, complex metaphors, wording, and a lack of guidance (Eskandari et al., 2018; Voskoboynikov et al., 2021), which all lead to a poor overall UX. Understanding how to design usable crypto-asset tools is an open research topic and better tools could lead to an increase in trust, which in turn, could positively influence both *Adoption Intention* and *Adoption Behavior*.

## 7 Limitations

This work has limitations that are commonly found in empirical studies in general. Clearly, the results of this study are not generalizable to the entire population of informed non-users. Further, over 60% of the non-user sample are females, who, as prior research has shown, usually perceive their technological skills lower than males (Hargittai and Shafer, 2006). Therefore, it is possible that the scores on the construct of self-efficacy could change in a more balanced sample.

With regard to internal validity, some of the constructs in our measurement model do not meet all the recommended thresholds found in literature. This work is the first quantitative analysis of crypto-asset non-users and the measurement reliability could be significantly improved. The differences between users and non-users need to be closely observed and more research needs to be conducted in order to understand how well non-users understand the associated risks and what severity they associate with them.

In this work, we only explore the institutional dimension of trust. Its importance was shown in prior qualitative work (Sas and Khairuddin, 2017; Voskoboynikov et al., 2020), however, other dimensions of trust, to the best of our knowledge, are left unexplored. Other trust constructs, including, but not limited to, *Dispositional Trust* (Tan and Sutherland, 2004), *Propensity to Trust* (Mcknight et al., 2011), and different *Trusting Bases* (Li, Hess, and Valacich, 2008) have been shown to have an effect and could therefore also influence one's decision concerning the crypto-asset adoption.

Lastly, all data was collected from participants residing in the U.S. Thus far, to the best of our knowledge, there exists no work highlighting the differences in crypto-asset usage behavior between countries. However, based on prior evidence suggesting that the cultural values play a role in technology acceptance (Srite and Karahanna, 2006), we believe that similar patterns might exist in the context of crypto-assets.

## 8 Conclusion

This study is the first empirical investigation of factors influencing the adoption behavior among non-users of crypto-assets. Drawing upon the results of the literature review, we have derived a theoretical model that explains the interactions between trust, self-efficacy, risk, and adoption intention.

Our results have showed a significant positive effect of trust on the adoption intention, and have further confirmed the interaction effects between the aforementioned constructs. We have provided recommendations on how to increase both self-efficacy and trust of non-users in order to lower the entry barriers and make the domain of crypto-assets more inclusive.

## References

- Abramova, S. and R. Böhme (2016). "Perceived Benefit and Risk as Multidimensional Determinants of Bitcoin Use: A Quantitative Exploratory Study." In: *Proceedings of the Thirty Seventh International Conference on Information Systems (ICIS)*. Dublin, Ireland.
- Akturan, U. and N. Tezcan (2012). "Mobile banking adoption of the youth market." *Marketing Intelligence & Planning*.
- Alalwan, A. A., Y. K. Dwivedi, N. P. Rana, B. Lal, and M. D. Williams (2015). "Consumer adoption of Internet banking in Jordan: Examining the role of hedonic motivation, habit, self-efficacy and trust." *Journal of Financial Services Marketing* 20 (2), 145–157.
- Alalwan, A. A., Y. K. Dwivedi, and N. P. Rana (2017). "Factors influencing adoption of mobile banking by Jordanian bank customers: Extending UTAUT2 with trust." *International Journal of Information Management* 37 (3), 99–110.
- Antonopoulos, A. M. (2014). *Mastering Bitcoin: unlocking digital cryptocurrencies*. " O'Reilly Media, Inc."
- Arias-Oliva, M., J. Pelegrín-Borondo, and G. Matías-Clavero (2019). "Variables Influencing Cryptocurrency Use: A Technology Acceptance Model in Spain." *Frontiers in Psychology* 10, 475.
- Astrachan, C. B., V. K. Patel, and G. Wanzenried (2014). "A comparative study of CB-SEM and PLS-SEM for theory development in family firm research." *Journal of Family Business Strategy* 5 (1), 116–128.
- Bandura, A. (2010). "Self-efficacy." *The Corsini encyclopedia of psychology*, 1–3.
- Baur, A. W., J. Bühler, M. Bick, and C. S. Bonorden (2015). "Cryptocurrencies as a Disruption? Empirical Findings on User Adoption and Future Potential of Bitcoin and Co." In: *Conference on e-Business, e-Services and e-Society*. Ed. by M. Janssen, M. Mäntymäki, J. Hidders, B. Klievink, W. Lamersdorf, B. van Loenen, and A. Zuiderwijk. Springer. Cham: Springer International Publishing, pp. 63–80.
- Bitcoin.com (2020). *The EU announces its first ever plan to regulate cryptocurrencies*. <https://www.cnbc.com/2020/09/24/eu-valdis-dombrovskis.html>. Accessed: 2020-11-17.
- Böhme, R., N. Christin, B. Edelman, and T. Moore (2015). "Bitcoin: Economics, Technology, and Governance." *Journal of Economic Perspectives* 29 (2), 213–38.
- Bohr, J. and M. Bashir (2014). "Who Uses Bitcoin? An exploration of the Bitcoin community." In: *Twelfth Annual International Conference on Privacy, Security and Trust*. IEEE. Toronto, Canada, pp. 94–101.
- Bonneau, J., A. Miller, J. Clark, A. Narayanan, J. A. Kroll, and E. W. Felten (2015). "SoK: Research Perspectives and Challenges for Bitcoin and Cryptocurrencies." In: *2015 IEEE Symposium on Security and Privacy*, pp. 104–121. DOI: 10.1109/SP.2015.14.
- Chiu, C.-M., E. T. Wang, Y.-H. Fang, and H.-Y. Huang (2014). "Understanding customers' repeat purchase intentions in B2C e-commerce: the roles of utilitarian value, hedonic value and perceived risk." *Information Systems Journal* 24 (1), 85–114.
- CoinMarketCap (2020). *Distinct Cryptocurrencies*. <https://coinmarketcap.com/all/views/all/>. Accessed: 2020-08-04.
- CoinTelegraph (2020). *OneCoin: A deep dive into crypto's most notorious Ponzi scheme*. <https://cointelegraph.com/news/onecoin-a-deep-dive-into-crypto-s-most-notorious-ponzi-scheme>. Accessed: 2020-11-11.
- Crosby, M., P. Pattanayak, S. Verma, V. Kalyanaraman, et al. (2016). "Blockchain technology: Beyond bitcoin." *Applied Innovation* 2 (6-10), 71.
- Das, T. and B.-S. Teng (2004). "The risk-based view of trust: A conceptual framework." *Journal of Business and Psychology* 19 (1), 85–116.
- Davis, F. D. (1989). "Perceived usefulness, perceived ease of use, and user acceptance of information technology." *MIS Quarterly*, 319–340.
- Delone, W. H. and E. R. McLean (2003). "The DeLone and McLean model of information systems success: a ten-year update." *Journal of management information systems* 19 (4), 9–30.

- Deutsche Welle (2020). *Africa's quiet cryptocurrency revolution*. <https://www.dw.com/en/africas-quiet-cryptocurrency-revolution/a-55199637>. Accessed: 2020-11-17.
- Eskandari, S., J. Clark, D. Barrera, and E. Stobert (2018). "A first look at the usability of bitcoin key management." *arXiv preprint arXiv:1802.04351*.
- Fornell, C. and D. F. Larcker (1981). *Structural equation models with unobservable variables and measurement error: Algebra and statistics*.
- Fröhlich, M., F. Gutjahr, and F. Alt (2020). "Don't lose your coin! Investigating Security Practices of Cryptocurrency Users." In: *Proceedings of the 2020 ACM Designing Interactive Systems Conference*, pp. 1751–1763.
- Gao, X., G. D. Clark, and J. Lindqvist (2016). "Of two minds, multiple addresses, and one ledger: characterizing opinions, knowledge, and perceptions of Bitcoin across users and non-users." In: *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*, pp. 1656–1668.
- Gefen, D., E. Karahanna, and D. W. Straub (2003). "Trust and TAM in online shopping: An integrated model." *MIS quarterly* 27 (1), 51–90.
- Grant, G. and R. Hogan (2015). "Bitcoin: Risks and Controls." *Journal of Corporate Accounting & Finance* 26 (5), 29–35.
- Gu, J.-C., S.-C. Lee, and Y.-H. Suh (2009). "Determinants of behavioral intention to mobile banking." *Expert Systems with Applications* 36 (9), 11605–11616.
- Hair, J. F., W. C. Black, B. J. Babin, R. E. Anderson, R. L. Tatham, et al. (1998). *Multivariate data analysis*. Vol. 5. 3. Prentice hall Upper Saddle River, NJ.
- Hanafizadeh, P., M. Behboudi, A. A. Koshksaray, and M. J. S. Tabar (2014). "Mobile-banking adoption by Iranian bank clients." *Telematics and Informatics* 31 (1), 62–78.
- Hanafizadeh, P., B. W. Keating, and H. R. Khedmatgozar (2014). "A systematic review of Internet banking adoption." *Telematics and informatics* 31 (3), 492–510.
- Hargittai, E. and S. Shafer (2006). "Differences in Actual and Perceived Online Skills: The Role of Gender." *Social Science Quarterly* 87 (2), 432–448. DOI: 10.1111/j.1540-6237.2006.00389.x.
- Henry, C. S., K. Huynh, and G. Nicholls (2018). "Bitcoin Awareness and Usage in Canada." *Journal of Digital Banking* 2 (4), 311–337.
- Henseler, J., C. M. Ringle, and M. Sarstedt (2015). "A new criterion for assessing discriminant validity in variance-based structural equation modeling." *Journal of the academy of marketing science* 43 (1), 115–135.
- Hileman, G. and M. Rauchs (2017). "Global Cryptocurrency Benchmarking Study." *Cambridge Centre for Alternative Finance* 33, 33–113.
- Hu, L.-t. and P. M. Bentler (1999). "Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives." *Structural equation modeling: a multidisciplinary journal* 6 (1), 1–55.
- ING (2018). *Cracking the code on cryptocurrency*. <https://think.ing.com/reports/cracking-the-code-on-cryptocurrency/>. Accessed: 2020-11-17.
- Jansen, J. (2015). "Studying Safe Online Banking Behaviour: A Protection Motivation Theory Approach." In: *HAISA*, pp. 120–130.
- Jeong, B. K., T. E. Yoon, et al. (2013). "An empirical investigation on consumer acceptance of mobile banking services." *Business and management research* 2 (1), 31–40.
- Khairuddin, I. E. and C. Sas (2019). "An Exploration of Bitcoin Mining Practices: Miners' Trust Challenges and Motivations." In: *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. Glasgow, Scotland, UK: Association for Computing Machinery, pp. 1–13. ISBN: 9781450359702.
- Khairuddin, I. E., C. Sas, S. Clinch, and N. Davies (2016). "Exploring motivations for bitcoin technology usage." In: *Proceedings of the 2016 CHI Conference Extended Abstracts on Human Factors in Computing Systems*, pp. 2872–2878.

- Kim, G., B. Shin, and H. G. Lee (2009). "Understanding dynamics between initial trust and usage intentions of mobile banking." *Information Systems Journal* 19 (3), 283–311.
- Kim, Y. H. and D. J. Kim (2005). "A study of online transaction self-efficacy, consumer trust, and uncertainty reduction in electronic commerce transaction." In: *Proceedings of the 38th Annual Hawaii International Conference on System Sciences*. IEEE, pp. 170c–170c.
- Kiran, M. and M Stanett (2015). "Bitcoin Risk Analysis." *NEMODE Policy Paper*.
- Kline, R. B. (2015). *Principles and practice of structural equation modeling*. Guilford publications.
- Krombholz, K., A. Judmayer, M. Gusenbauer, and E. Weippl (2016). "The Other Side of the Coin: User Experiences with Bitcoin Security and Privacy." In: *Financial Cryptography and Data Security*. Ed. by J. Grossklags and B. Preneel. Berlin, Heidelberg: Springer Berlin Heidelberg, pp. 555–580.
- Lai, V. S. and H. Li (2005). "Technology acceptance model for internet banking: an invariance analysis." *Information & management* 42 (2), 373–386.
- Lee, K. S., H. S. Lee, and S. Y. Kim (2007). "Factors influencing the adoption behavior of mobile banking: a South Korean perspective." *The Journal of Internet Banking and Commerce* 12 (2), 1–9.
- Li, X., T. J. Hess, and J. S. Valacich (2008). "Why do we trust new technology? A study of initial trust formation with organizational information systems." *The Journal of Strategic Information Systems* 17 (1), 39–71.
- Liu, Z., Q. Min, and S. Ji (2009). "An empirical study on mobile banking adoption: The role of trust." In: *2009 Second International Symposium on Electronic Commerce and Security*. Vol. 2. IEEE, pp. 7–13.
- Luarn, P. and H.-H. Lin (2005). "Toward an understanding of the behavioral intention to use mobile banking." *Computers in human behavior* 21 (6), 873–891.
- Luo, X., H. Li, J. Zhang, and J. P. Shim (2010). "Examining multi-dimensional trust and multi-faceted risk in initial acceptance of emerging technologies: An empirical study of mobile banking services." *Decision support systems* 49 (2), 222–234.
- Mai, A., K. Pfeffer, M. Gusenbauer, E. Weippl, and K. Krombholz (2020). "User Mental Models of Cryptocurrency Systems – A Grounded Theory Approach." In: *Sixteenth Symposium on Usable Privacy and Security (SOUPS)*, pp. 341–358.
- Makanyeza, C. (2017). "Determinants of consumers' intention to adopt mobile banking services in Zimbabwe." *International Journal of Bank Marketing*.
- Marakarkandy, B., N. Yajnik, and C. Dasgupta (2017). "Enabling internet banking adoption." *Journal of Enterprise Information Management*.
- Marsh, H. W. and D. Hocevar (1985). "Application of confirmatory factor analysis to the study of self-concept: First-and higher order factor models and their invariance across groups." *Psychological bulletin* 97 (3), 562.
- Martins, C., T. Oliveira, and A. Popovič (2014). "Understanding the Internet banking adoption: A unified theory of acceptance and use of technology and perceived risk application." *International Journal of Information Management* 34 (1), 1–13.
- McIver, J. and E. G. Carmines (1981). *Unidimensional scaling*. 24. Sage.
- Mcknight, D. H., M. Carter, J. B. Thatcher, and P. F. Clay (2011). "Trust in a specific technology: An investigation of its components and measures." *ACM Transactions on management information systems (TMIS)* 2 (2), 1–25.
- Moore, T., N. Christin, and J. Szurdi (2018). "Revisiting the risks of bitcoin currency exchange closure." *ACM Transactions on Internet Technology (TOIT)* 18 (4), 1–18.
- Mun, Y. Y. and Y. Hwang (2003). "Predicting the use of web-based information systems: self-efficacy, enjoyment, learning goal orientation, and the technology acceptance model." *International journal of human-computer studies* 59 (4), 431–449.
- Nakamoto, S. (2008). *Bitcoin: A Peer-to-Peer Electronic Cash System*.
- Narayanan, A., J. Bonneau, E. Felten, A. Miller, and S. Goldfeder (2016). *Bitcoin and cryptocurrency technologies: a comprehensive introduction*. Princeton University Press.



- Nguyen, Q. N. and D. J. Kim (2017). “Enforcing Information Security Protection: Risk Propensity and Self-Efficacy Perspectives.” In: *Proceedings of the 50th Hawaii International Conference on System Sciences*.
- NYTimes (2017). *CryptoKitties, Explained ... Mostly*. <https://www.nytimes.com/2017/12/28/style/cryptokitties-want-a-blockchain-snuggle.html>. Accessed: 2020-11-12.
- Pavlou, P. A. (2003). “Consumer acceptance of electronic commerce: Integrating trust and risk with the technology acceptance model.” *International journal of electronic commerce* 7 (3), 101–134.
- Pikkarainen, T., K. Pikkarainen, H. Karjaluoto, and S. Pahnla (2004). “Consumer acceptance of online banking: an extension of the technology acceptance model.” *Internet research*.
- Presthus, W. and N. O. O’Malley (2017). “Motivations and barriers for end-user adoption of bitcoin as digital currency.” *Procedia Computer Science* 121, 89–97.
- Rauchs, M., A. Blandin, K. Klein, G. C. Pieters, M. Recanatini, and B. Z. Zhang (2018). “2nd Global Cryptoasset Benchmarking Study.” Available at SSRN 3306125.
- Riegelsberger, J., M. A. Sasse, and J. D. McCarthy (2005). “The mechanics of trust: A framework for research and design.” *International Journal of Human-Computer Studies* 62 (3), 381–422.
- Riek, M., S. Abramova, and R. Böhme (2017). “Analyzing Persistent Impact of Cybercrime on the Societal Level: Evidence for Individual Security Behavior.” In: *ICIS*.
- Rosseel, Y. (2012). “Lavaan: An R package for structural equation modeling and more. Version 0.5–12 (BETA).” *Journal of statistical software* 48 (2), 1–36.
- Roy, S. K., A. Kesharwani, and S. S. Bisht (2012). “The impact of trust and perceived risk on internet banking adoption in India.” *International Journal of Bank Marketing*.
- Sas, C. and I. E. Khairuddin (2017). “Design for Trust: An Exploration of the Challenges and Opportunities of Bitcoin Users.” In: *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*. CHI ’17. Denver, Colorado, USA: ACM, pp. 6499–6510. ISBN: 978-1-4503-4655-9. DOI: 10.1145/3025453.3025886. URL: <http://doi.acm.org/10.1145/3025453.3025886>.
- Sharma, S. K. and M. Sharma (2019). “Examining the role of trust and quality dimensions in the actual usage of mobile banking services: An empirical investigation.” *International Journal of Information Management* 44, 65–75.
- Srite, M. and E. Karahanna (2006). “The role of espoused national cultural values in technology acceptance.” *MIS quarterly*, 679–704.
- Stix, H. (2019). *Ownership and purchase intention of crypto-assets – survey results*. Oesterreichische Nationalbank Working Papers (Austria).
- Tan, F. B. and P. Sutherland (2004). “Online consumer trust: a multi-dimensional model.” *Journal of Electronic Commerce in Organizations (JECO)* 2 (3), 40–58.
- Venkatesh, V. and F. D. Davis (2000). “A theoretical extension of the technology acceptance model: Four longitudinal field studies.” *Management science* 46 (2), 186–204.
- Voskoboynikov, A., B. Obada-Obieh, Y. Huang, and K. Beznosov (2020). “Surviving the Cryptojungle: Perception and Management of Risk Among North American Cryptocurrency (Non) Users.” In: *International Conference on Financial Cryptography and Data Security*. Springer, pp. 595–614.
- Voskoboynikov, A., O. Wiese, M. Mehrabi-Koushki, V. Roth, and K. Beznosov (2021). “The U in Crypto Stands for Usable: An Empirical Study of User Experience with Mobile Cryptocurrency Wallets.” In: *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*.
- Walton, A. and K. Johnston (2018). “Exploring perceptions of bitcoin adoption: the South African virtual community perspective.” *Interdisciplinary Journal of Information, Knowledge & Management* 13.
- Wood, G. et al. (2014). *Ethereum: A Secure Decentralised Generalised Transaction Ledger*. Tech. rep. Ethereum Project Yellow Paper, pp. 1–32.
- Yousafzai, S. Y., J. G. Pallister, and G. R. Foxall (2005). “Strategies for building and communicating trust in electronic banking: A field experiment.” *Psychology & Marketing* 22 (2), 181–201.
- Zhou, T. (2012). “Understanding users’ initial trust in mobile banking: An elaboration likelihood perspective.” *Computers in Human Behavior* 28 (4), 1518–1525.