İzmir İktisat Dergisi
İzmir Journal of Economics

**E-ISSN:** 1308-8505 **Year:** 2024 **Vol:** 39 **No:** 3 **Pages:** 733-754
**Received:** 22.11.2023 **Accepted:** 26.04.2024 **Published Online:** 09.07.2024 **Doi:** 10.24988/ije.1394574
**RESEARCH ARTICLE**

# Examining the Factors Affecting the Use of Crypto Assets as Foreign Payment and Investment Instruments: A Quantitative Study [1]

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**Abstract**

*The aim of the study is to examine the factors affecting individuals' intentions to use crypto assets as foreign payment and investment instruments. A research model based on the UTAUT-2, a widely accepted model that examines individuals' attitudes toward information technologies, was formed, and the factors affecting two dependent variables, "intention to use in foreign payments" and "intention to invest," were analyzed with PLS-SEM. Path coefficients (β) demonstrated that the variables significantly affecting the intention to use in foreign payments were "performance expectancy," "social influence," and "perceived risk," respectively. Moreover, in order of importance, "performance expectancy," "social influence," "awareness," and "perceived risk" were determined as the variables significantly affecting the intention to invest. Along with path coefficients, $f^2$ and $q^2$ effect sizes were also analyzed to examine the interaction between the variables. In the context of empirical findings, it was evaluated that the most significant factors in the participants' tendency to use crypto assets in foreign payments and investment transactions were "performance expectancy" and "social influence". Contrary to the widespread approach in the literature, the study has revealed crucial results for the literature and future studies by addressing the two main financial functions of crypto assets and the factors significantly affecting these functions.*

***Keywords:*** *Crypto Asset, Cryptocurrency, UTAUT-2, Fintech*
***Jel Codes:*** *F39, G10, G29*

## *Yurtdışı Ödeme ve Yatırım Aracı Olarak Kripto Varlıkların Kullanımını Etkileyen Faktörlerin İncelenmesi: Nicel Bir Araştırma*

***Özet***

*Çalışmanın amacı, bireylerin yurtdışı ödeme ve yatırım aracı olarak kripto varlıkları kullanma niyetlerini etkileyen faktörleri incelemektir. Bilgi teknolojilerine yönelik bireysel tutumları irdeleyen ve yaygın bir biçimde kabul görmüş olan UTAUT-2'ye dayalı bir araştırma modeli oluşturularak, "yurt dışı ödemelerde kullanım niyeti" ve "yatırımda bulunma niyeti" olmak üzere iki bağımlı değişkeni etkileyen faktörler PLS-SEM ile analiz edilmiştir. Yol katsayıları (β), yurt dışı ödemelerde kullanım niyetini anlamlı düzeyde etkileyen değişkenlerin sırasıyla "performans beklentisi", "sosyal etki" ve "algılanan risk" olduğunu göstermiştir. Ayrıca önem sırasına göre "performans beklentisi", "sosyal etki", "farkındalık" ve "algılanan risk", yatırımda bulunma niyetini anlamlı ölçüde etkileyen değişkenler olarak belirlenmiştir. Yol katsayılarının yanı sıra değişkenler arasında etkileşimi incelemek amacıyla $f^2$ ve $q^2$ etki büyüklükleri de analiz edilmiştir. Elde edilen bulgular bağlamında katılımcıların yurt dışı ödeme ve yatırım işlemlerinde kripto varlıkları kullanma eğilimlerini etkileyen en önemli faktörlerin "performans beklentisi" ve "sosyal etki" olduğu yönünde değerlendirme yapılmıştır. Çalışma, literatürdeki yaygın yaklaşımın aksine kripto varlıkların iki temel finansal işlevini ve bu işlevleri anlamlı ölçüde etkileyen faktörleri ele alarak, literatür ve gelecek çalışmalar için önemli sonuçlar ortaya koymuştur.*

***Anahtar kelimeler:*** *Kripto Varlık, Kripto-Para, UTAUT-2, Fintek*
***Jel Kodu:*** *F39, G10, G29*

[1] The study is a reviewed and translated compilation of the quantitative research conducted in a doctoral dissertation accepted in 2022 at Alanya Aladdin Keykubat University, Graduate School of Education, Department of International Trade.

**CITE (APA):** Yılmaz, G. & Koç, T.S. (2024). Examining the factors affecting the use of crypto assets as foreign payment and investment instruments: a quantitative study, *İzmir İktisat Dergisi,* 39(3), 733-754, Doi:10.24988/ije.1394574

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# 1. INTRODUCTION

Crypto assets, which first emerged in 2009 with Bitcoin, are innovative digital units that rely on cryptography to conduct transactions and unit issuance. With the introduction of other crypto-assets following Bitcoin, an ecosystem of crypto-asset exchanges, networks, and service providers emerged. Crypto assets contradict existing practices and processes regarding their functions and technical infrastructure. The most prominent feature of crypto assets is that they are built on cryptography (encryption) and blockchain. In addition, there is no need for approval or supervision of central institutions for the confirmation of transactions in crypto-asset networks. Transactions between parties are confirmed and verified by miners involved in crypto-asset networks. For this reason, it is possible to make transactions such as payments, investments, and savings independently of the components of the current financial system.

Sharing of credentials is not a requirement to make transactions with crypto assets. Individuals can use and transact crypto assets with proper wallet software and an internet connection. Due to this, implementing legal regulations and supervision of official institutions becomes a challenge for crypto assets. Nevertheless, due to the high volatility in their exchange rates, crypto assets have gained a prominent place on the world agenda. While the high volatility transforms some crypto assets into risky investment instruments, others can function as payment and saving tools with exchange rates pegged to national currencies. Although the crypto assets on the market have technically different software architectures, they generally have two essential functions: payment and investment instruments.

The fact that crypto assets have gained popularity with the rise in exchange rates also accelerated discussions on their opportunities and threats. Individuals' attitudes toward crypto assets and the factors affecting these attitudes can be taken as an essential component of these discussions. In other words, it would be helpful to examine why individuals tend to use crypto-assets and which factors affect their tendency in this direction. Previous studies in the literature on the subject are limited, and in general, other studies have focused on individual attitudes toward crypto assets from the viewpoint of general-purpose use without considering the usage areas of the crypto assets. A new research approach that considers the usage areas of crypto assets in this direction could be beneficial. In this context, the study aims to examine the factors affecting individuals' attitudes toward using crypto assets as payment and investment instruments. In line with the purpose of the research, a research model was created within the framework of UTAUT-2, which found widespread use in the literature, and the data were analyzed with PLS-SEM based structural equation modeling (SEM).

# 2. KEY FEATURES OF CRYPTO ASSETS

Crypto asset units operate on their internet networks, or, in other words, crypto asset systems. *A crypto asset system* can be defined as a computer network in which encryption techniques are used in all kinds of transactions and transactions are recorded in a digital ledger. Crypto asset units are produced in these networks and used to conduct transactions. (Pernice & Scott, 2021: 2). Crypto assets are developed independently of the official institutions of the countries and are generally outside these institutions' supervision and surveillance activities (EBA, 2019: 11). In addition, difficulties are encountered in terms of crypto assets in the application of current legal regulations. The uniqueness of crypto assets in terms of their technical characteristics is an essential factor that makes it difficult for them to comply with current regulations. For this reason, it is necessary to make new and appropriate regulations that consider the technical features of crypto assets (Bolotaeva et al., 2019: 3).

Although issues related to legal regulations threaten the legal security of individuals, crypto assets have been a phenomenon worldwide and have gained a large scale of popularity. The question of "for what purposes" individuals or corporations use crypto assets reveals the usage areas of crypto assets.

The report published by the Organization for Economic Cooperation and Development (OECD) regarding this issue includes a unique classification of crypto assets. In this classification, crypto assets are divided into three categories: payment, investment, and utility units (OECD, 2020: 12):

**Table 1.** A Classification for the Usage Areas of Crypto Assets[1]

| Category | Definition |
|---|---|
| ***Payment Units*** | In parallel to national currencies, these crypto assets serve as payment, saving, or unit of account (pricing) instruments. |
| ***Investment Units*** | Crypto assets that are used for investment purposes. Investment units can also qualify as "securities" if they are defined in national regulations. |
| ***Utility Units*** | Types of crypto assets whose primary function is to provide access to internet-based products or services, and which enable their owners to do so. |

**Source:** (OECD, 2020: 12)

The "payment" and "investment" units in Table 1 correspond to crypto assets' two essential financial functions. Utility units primarily serve as intermediate units for applications in crypto-asset networks rather than directly providing financial services. The purpose of utility units is to provide access to applications on crypto asset networks. Holders of these units can access voting, trading packages, or reward programs in the relevant applications (Angelo & Salzer, 2020: 2). When the utility units are excluded from the scope, it can be stated that crypto assets have two primary functions: to function as payment or investment instruments. Regarding which of these functions is more suitable for crypto assets, the volatility in exchange rate values stands out as an essential indicator. The exchange rates of crypto assets such as Bitcoin and Ethereum are related to supply and demand in market conditions, and high levels of change can be seen in short periods[2].

Crypto assets with highly volatile exchange rates pose inconveniences regarding the functions of money. For any digital or physical element to be accepted as "money" or "means of payment," it must carry the functions of money. Throughout its historical development, the main functions of money have been as a medium of exchange, store of value, and unit of account. (Mishkin, 1992: 22). When any unit with a highly volatile exchange rate is used as a payment instrument, the parties of the payment could face foreign exchange losses due to instant exchange rate changes. A similar situation is valid for the functions of money as a store of value and unit of account. High rate decreases in the unit's exchange rate may cause a loss of savings. Also, when used as a unit of account, the prices will need to be updated continuously and instantly due to the fluctuation in the exchange rate. In this context, it is possible to state that crypto assets such as Bitcoin and Ethereum are in demand for investment purposes rather than as payment instruments, and they are risky investment instruments due to the fluctuations in exchange rates.[3]

Units with more stable exchange rates, which differ from the examples given above, have also emerged in crypto asset markets. These are traded by pegging the exchange rates of national

[1] A similar classification is also included in a report published by the European Banking Authority (EBA) (EBA, 2019: 7).

[2] The web platform coinmparketcap.com, which includes market data on crypto assets, demonstrates the crypto assets' high exchange rate fluctuations (www.coinmarketcap.com).

[3] A study conducted by Baur et al. (2017) on the subject and based on market data between 2010 and 2015 showed that Bitcoin differs highly from national currencies regarding the exchange rate. Within the scope of the study, the data of the Bitcoin network was also examined, and it was seen that one-third of the Bitcoin amount in circulation was kept constant and was not subject to transmission transactions. Considering the findings, it was concluded that few users use Bitcoin as a payment instrument (Baur et al., 2017: 5–15). On the other hand, survey-based research by ING Bank in 15 countries, including Türkiye, found that only 35% of participants think that Bitcoin will be a payment instrument for spending online in the future (ING, 2018: 12).

currencies or other financial instruments, and they offer exchange rates equivalent to their pegging national currency or other instruments. (Berensten & Schär, 2019: 65–66). It can be stated that crypto assets pegged to investment instruments such as gold and stocks are traded for investment purposes, such as Bitcoin and Ethereum. In other words, these crypto assets provide functions in parallel with the investment instrument they are linked to and are used by individuals for investment purposes. On the other hand, crypto assets pegged to the exchange rates of national currencies (also called *stablecoins*) procure an appropriate use in terms of the functions of money. They are thus compatible to serve as means of payment, store of value, or unit of account. Crypto assets, which offer exchange value equivalent to national currencies, mainly USD, can also be considered "crypto asset-based derivatives" of national currencies.

It is also worth mentioning the advantages that have become evident in terms of transaction time and fee while using crypto assets as a payment instrument. These advantages are significant for payments to be made abroad, as there are fast and low-cost options for domestic payments with internet banking[1]. Crypto asset networks allow crypto asset transfers with high transaction speeds and low fees. Regarding this issue, the data on the transaction fee and time of the Ethereum network can be examined because USDT, USDC, and BUSD, examples of crypto assets pegged to the exchange rates of national currencies, are produced as sub-units (tokens) in the Ethereum network. The transaction fee and time figures of Ethereum are also valid for the transfers of units that function as sub-units in the network. According to data for 2023 (until November 14), the cost for the sender of transfers on the Ethereum network ranged from $0.38 to $3.79 ( https://ycharts.com/indicators/ethereum average transaction fee ). The completion time of transactions on the Ethereum network for the date of 14 November 2023 was approximately 30 seconds ( https://etherscan.io/gatracker ). According to these data, crypto assets may be more advantageous than foreign banking transfers[2]. Therefore, crypto assets pegged to the exchange rates of national currencies can be accepted as efficient alternatives for international payment transactions. However, in today's circumstances, it is unlikely to state that crypto assets offer sufficient transaction security, both legally and technically, in terms of their acceptance.

With the assessments and opinions above, as payment and investment instruments, two main functions of crypto assets were emphasized and examined. In fact, there may be technically different functions and qualities of crypto assets. However, related financial functions are prominent, and it can be said that they are in demand for these functions. The question of which factors affect the attitude of individuals to use crypto assets as a means of payment or investment constitutes the purpose of the research. Crypto assets differ from traditional payment and investment instruments in that they are traded on decentralized networks and offer the opportunity to transact without needing identity information. Examining the factors that affect individuals' preference for crypto assets instead of the usual and currently in-use payment and investment instruments is a significant issue contributing to the literature and the field of application. In this review, it is helpful to consider the advantages of crypto assets in terms of transaction fees and time and to examine individual attitudes toward international payments. In this direction, firstly, other studies in the literature were examined to determine the method and research model suitable for the research.

[1] By using the FAST system in Türkiye, which serves as an inter-bank payment system within the Central Bank (TCMB), payments can be made instantly and cost-effectively, without any day or hour limitation (https://fast.tcmb.gov.tr/).

[2] For instance, in foreign currency transfers (SWIFT) to be sent abroad via T.C. Ziraat Bank account (a commercial bank in Türkiye), a transaction fee of 20$ to 500$ is charged for sending 250$ or more, excluding other costs related to international transfers. (https://www.ziraatbank.com.tr/tr/urun-ve-hizmet-ucretleri ).

## 3. LITERATURE REVIEW

With the increase in exchange rates and market volumes, discussions on crypto assets and academic studies on crypto assets have gained momentum. A literature review was conducted to examine other studies examining individuals' attitudes towards crypto assets, and the studies shown in Table 2 were examined. Structural equation modeling, one of the multivariate statistical techniques, was adopted in all those studies, and analyses were carried out on the primary data collected with questionnaires. The reviewed studies are based on UTAUT-2 (Unified Theory of Acceptance and Use of Technology-2), UTAUT (Unified Theory of Acceptance and Use of Technology), and TAM (Technology Acceptance Model), which are interrelated research models and examine the acceptance of new technology products and services. Table 2 presents brief information on related studies' research models, determination coefficients ($R^2$), and significant findings.

**Table 2.** Contents and Findings of the Examined Studies

| # | Independent Variables | Dependent Variable | ($R^2$) | Significant Results, in order of importance (p<0.05) |
|---|---|---|---|---|
| Arias-Oliva et al. (2019) | *Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Perceived Risk, Financial Literacy* | Intention to Use | 0.848 | Performance Expectancy (β=0.764), Facilitating Conditions (β=0.220), |
| Gillies et al. (2020) | *Effort Expectancy, Facilitating Conditions, Performance Expectancy, Social Influence** | Intention to Use Bitcoin | 0.642 | Performance Expectancy (β=0.453), Social Influence (β=0.263), Facilitating Conditions (β=0.179) |
| Shahzad et al. (2018) | *Awareness, Perceived Ease of Use, Perceived Usefulness, Perceived Trustworthiness* | Intention to Use Bitcoin | 0.51 | Perceived Trustworthiness (β=0.330), Perceived Usefulness (β=0.236), Awareness (β=0.229), Perceived Ease of Use (β=0.125) |
| Lee et al. (2018) | Profitability Expectancy, Trust (*Asset Attitude)*, Perceived Usefulness, Perceived Ease of Use, Transaction Compatibility (*Currency Attitude) *** | Intention to Adopt | 0.631 | Asset Attitude (β=0.672), Profitability Expectancy (β=0.465), Perceived Usefulness (β=0.391), Trust (β=0.379), Transaction Compliance (β=0.272), Currency Attitude (β=0.272) |

* The mediating role of five different demographic characteristics (age, gender, ethnicity, education, and income level) in the interaction between independent and dependent variables was also examined.
** In the research model, Asset Attitude and Currency Attitude are both dependent and independent variables. A structural model was created in which Profitability Expectancy and Trust affect Asset Attitude and other dimensions affect Currency Attitude. The interaction between these two dimensions and the intention to adopt was also examined.

In the study of Arias-Oliva et al. (2019: 8-9), a research model in which UTAUT-2 is referenced was used. UTAUT-2 is a multivariate research model that examines individuals' attitudes toward information technologies (Venkatesh et al., 2012: 157-158). When the literature is examined, it is observed that UTAUT-2 is widely used in studies examining individual attitudes toward technology products and services. UTAUT, the predecessor of the UTAUT-2, was developed within the scope of a study published in 2003 (Venkatesh et al., 2003: 426–427). A research model parallel to the UTAUT was adopted in the study of Gillies et al. (2020), one of the reviewed studies in Table 2 (Gillies et al., 2020: 30). In the other two studies in Table 2, research models based on the TAM model and other studies in the literature were adopted (Shahzad et al., 2018: 35; Lee et al., 2018: 51). The TAM model developed by Davis (1989) deals with the attitudes of individuals towards technology products and forms the basis for UTAUT and UTAUT-2 (Davis, 1989: 320–332). As mentioned above, all three models are theoretically interacting with each other. UTAUT-2, on the other hand, can be considered an updated and improved version of the other two models in terms of examining individual attitudes towards information technologies.

Studies in Table 2 are not based on how often individuals use crypto assets but on to what extent they tend to use crypto assets. "Use behavior", which corresponds to the actual use of the relevant technology in UTAUT and UTAUT-2, was not included in the research models of the examined studies. This approach can be considered appropriate for innovative technologies such as crypto assets. Although individuals have never used crypto assets, they may be inclined to use them soon. Therefore, more convenient results can be obtained with a research model based on usage intentions. On the other hand, in the study of Lee et al. (2018), the dimensions corresponding to the two primary functions of crypto assets: payment and investment instruments, are included in the research model (asset attitude and currency attitude). This distinction, which was also emphasized within the scope of this study, was found relevant in terms of crypto-asset-based research. In addition, Lee et al. (2018) also examined the interaction between dimensions related to these functions and the intention to adopt Bitcoin (Lee et al., 2018: 51-53).

Considering its theoretical background and acceptance in the literature, UTAUT-2 offers a suitable area for research on innovative technology products such as crypto assets. In the context of the literature review, it was decided to develop a research model in which the UTAUT-2 model was taken as a reference and examine individuals' behavioral intentions, as in the studies in Table 2. Parallel to the approach of Lee et al. (2018), a research model based on the two main usage areas of crypto assets (payment and investment) was created. It was accepted that an approach based on foreign payment transactions would be beneficial due to the advantages of transaction fees and time savings in using crypto assets as payment instruments.

## 4. METHODOLOGY

The quantitative research method was adopted within the scope of the study, and survey forms were used as data collection tools. Structural Equation Modeling (SEM) was used to analyze the data, the same as the UTAUT-2 model and studies in Table 2. SEM is a multivariate statistical technique that allows examining the relationships between dependent and independent variables and includes methods such as causality tests, equation modeling, path analysis, and confirmatory factor analysis (Ullman & Bentler, 2013: 661).

Two SEM methods, "Covariance Based Structural Equation Modeling" (CB-SEM) and "Partial Least Squares Structural Equation Modeling" (PLS-SEM), are widely adopted in the literature. The CB-SEM method is based on a covariance matrix to analyze the relationship between the variables. In addition, normal distribution is a prerequisite for this technique. In the PLS-SEM method, the interaction between the variables is examined by the variance observed in the dependent variables. An essential advantage of the PLS-SEM method for researchers is that it does not require a normal distribution of data (Hair et al., 2017: 4–10; Kock, 2017: 4–5). Since PLS-SEM was adopted in the study in which the UTAUT-2 model was developed (Venkatesh et al., 2012), as well as in the other works in Table 2 (Arias-Oliva et al., 2019; Lee et al., 2018), it was decided to use PLS-SEM in this research.

A research model based on UTAUT-2 was developed, and following the research purpose, "hedonic motivation" and "price value" as two of UTAUT-2 constructs were excluded from the research model. For information technologies, hedonic motivation corresponds to the happiness or enjoyment of using a technology product or service (Tamilmani et al., 2019: 223). Hedonic motivation can be decisive in trends toward products and services such as computer games, mobile devices, and social media applications. However, it was accepted that hedonic motivation would not be valid for financial products or services such as crypto assets. Similarly, the "price value" in the UTAUT-2 model was not considered in the research model. *Price value* can be defined as the level of perception of the individual towards the cost of the technology product. Crypto assets are not products or services that are subject to final consumption. For this reason, price value is inappropriate for studies on crypto assets.

Along with excluded variables, the research model contains three different variables than UTAUT-2: "awareness," "computer self-efficacy," and "perceived risk." Awareness is an individual's self-evaluation of his or her level of knowledge about the relevant technology, product, or service. As seen in Table 2, awareness is an independent variable in the study of Shahzad et al. (2018), and it was observed that *awareness* positively affected the *intention to use Bitcoin* (Shahzad et al., 2018: 35–38). The technically complex nature of crypto assets and the continuation of their development processes lie behind including such a dimension in the research model.

Another variable included in the research model is "computer self-efficacy." To use and store crypto assets, basic computer skills are necessary for individuals. There is no possibility to undo crypto-asset transactions, and due to misuse, crypto-assets may be stolen or become out of use. For this reason, it can be helpful to consider the personal perceptions of individuals regarding their computer skills. In the literature, it was seen that computer self-efficacy was adopted as an independent variable in a study based on the UTAUT model, which is subject to web-based learning services (Chiu & Wang, 2008: 95-196).

Perceived risk is the third of the research model's variables that differ from UTAUT-2. Due to the risks related to the exchange rates and usage patterns of crypto assets, it was accepted that including "perceived risk" would be beneficial. Thus, in Table 2, the effect of perceived risk on intention to use is examined in Arias-Oliva et al.'s (2019) study (Arias-Oliva et al., 2019: 5).

Along with the mentions above, *habit*, one of the UTAUT-2 model's variables, was revised to "legacy system habit" and included in the research model. In UTAUT-2, habit is a construct that corresponds to individuals' use of technology automatically. Venkatesh et al. (2016) stated that legacy system habits may affect attitudes toward technology products and services and suggested this dimension for future UTAUT-2-based studies (Venkatesh et al., 2016: 346–350). *Legacy system habit* can be defined as the tendency to use the technology that is currently in use despite its new alternatives. Regarding crypto assets, it is possible to consider the existing payment and investment instruments as the "legacy system." Considering individuals' tendencies towards traditional payment and investment instruments, it was decided to add this dimension to the model to examine their intention to use crypto assets.

The research model has two dependent variables about using crypto assets as payment or investment tools. The "behavioral intention" in the UTAUT-2 model, which is also defined as the tendency to use the technology product, forms the basis of the dependent variables. As in the studies examined in Table 2, the research model did not consider the "use behavior" corresponding to the frequency of use of the relevant technology product. As explained in the previous title with justifications, an approach based on international payment transactions was adopted in the first of the dependent dimensions. It aimed to measure the intention of individuals to use crypto assets in international payments for various purposes. This dimension is named "intention to use in foreign payments." Secondly, "intention to invest" was included in the research model as a dependent variable corresponding to the functioning of crypto assets as investment instruments and focused on individuals' tendencies to invest in crypto assets.

The research model examines the interaction between eight independent and two dependent variables. The data collection tool created in this direction consists of 42 survey items and is a 5-

point Likert-type scale[1]. In the survey items, the scale of the UTAUT-2 model and other studies in the literature were used. The explanations regarding the constructs of the research model and the survey items are as follows[2]:

• Awareness (FRK): AW aims to measure the awareness perceptions of individuals towards crypto assets. In total, four propositions were used. Items FRK1 and FRK4 were adapted from Shahzad et al.'s (2018: 38) study. FRK2 and FRK3 were developed within the scope of this research.

• Computer Self-Efficacy (BİL): It measures individuals' self-efficacy perceptions towards their computer skills and consists of five items. The scale developed by Howard (2014: 681) is based on the first four survey items regarding computer self-efficacy (BİL1, BİL2, BİL3, BİL4). Thus, BİL5 was developed within the scope of this research.

• Performance Expectancy (PEB): PE is included in the model to measure individual perceptions that crypto assets will offer financial efficiency. Three of the items (PEB1, PEB2, PEB3) were adapted from the study of Yuen et al. (2010), and the fourth item (PEB4) was formed by adapting the UTAUT-2 scale (PE1).

• Effort Expectancy (ÇB): This construct corresponds to the level of individual perception of how much effort it will take to make transactions with crypto assets. Four items of effort expectancy were adapted from the scale used in the study of Arias-Oliva et al. (2019: 6).

• Facilitating Conditions (KK): KK aims to measure individuals' perceptions of personal and environmental conditions that facilitate the use of crypto assets. KK consists of five items. KK1, KK2, KK4, and KK5 were adapted from the UTAUT-2 scale (Venkatesh et al., 2012), and KK3 was developed within the scope of this research.

• Perceived Risk (AR): Perceived risk measures individuals' risk perceptions regarding crypto assets. The first three items were based on the scale used in Alias-Oliva et al.'s (2019) study (AR1, AR2, and AR3), while AR4 is an adaptation of "PT3", a survey item in the study of Shahzad et al. (2018: 38).

• Social Influence (SE): The scale used by Yuen et al.'s (2010) is a basis for items SE1, SE3, and SE4. On the other hand, SE2 was created by adapting the UTAUT2 scale's relevant items.

• Legacy System Habit (ESA): Four items were developed in the context of the UTAUT-2 model's habit construct. The items of the ESA cover the tendency to use other traditional payment and investment instruments in contrast to crypto assets.

• Intention to Use in Foreign Payments (YÖN): Formed by adapting the behavioral intention dimension in UTAUT-2 and includes four items. The measurement tool in the study of Yuen et al.

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[1] In the measurement tool of the research, the definition of "cryptocurrency" is used instead of "crypto asset" in all items. In fact, it can be concluded that the definition of "crypto asset" is more appropriate for cryptography and blockchain-based digital units because the definition of "cryptocurrency" causes a connotation that all crypto assets are suitable for money functions. The definition of "crypto asset" may cover all digital units based on blockchain and cryptography under a common concept, regardless of their compatibility with money functions. However, as seen in the literature and popular publications, the definition of "cryptocurrency" is also widely used to name the relevant digital units. The "crypto asset" approach was recently adopted on the axis of international organizations and legal regulations. In this study, it was accepted that using the definition of "cryptocurrency" would be more beneficial to prevent a false connotation for the individuals.

[2] The propositions (items) in the data collection tool are generated in Turkish. All items are presented in the Appendix. The abbreviations of the variables correspond to Turkish equivalents: Awareness (Farkındalık)=FRK; Computer Self-Efficacy (Bilgisayar Öz-Yeterliği)=BİL; Performance Expectancy (Performans Beklentisi)=PEB; Effort Expectancy (Çaba Beklentisi)=ÇB; Facilitating Conditions (Kolaylaştırıcı Koşullar)=KK; Perceived Risk (Algılanan Risk)=AR; Social Influence (Sosyal Etki)=SE; Legacy System Habit (Eski Sistem Alışkanlığı)=ESA; Intention to Use in Foreign Payments (Yurtdışı Ödemelerde Kullanım Niyeti)=YÖN; Intention to Invest (Yatırımda Bulunma Niyeti)=YTB.

(2010: 56) was also used for the propositions. Generally, items are based on three international transactions: product orders, service orders, and money transfers.

• Intention to Invest (YTB): As another dependent variable of the research model, YTB includes four items. Based on the behavioral intention of UTAUT-2, YTB was formed to measure the tendency of individuals to invest in crypto assets.

The population for the research was selected to include individuals with expertise and experience in foreign payments and investment instruments. In this direction, the staff working in banks in Türkiye and faculty members working in the banking, finance, and international trade departments comprised the population. A total of 504 responses were made to the questionnaire distributed online using the random sampling technique, and 26 forms with inconsistent answers were excluded from the scope. Hence, the sample of the research consists of 478 individuals.

## 5. FINDINGS

Primarily, the validity and reliability of the data collection tool, also called the measurement model, were determined. Due to the research model and a data collection tool adapted from other studies in the literature, the validity and reliability of the data collection tool were examined by confirmatory factor analysis. In this direction, the approach suggested in the work of Hair et al. (2017: 106) was adopted, and data collection was examined in terms of internal consistency reliability, convergent validity, discriminant validity, and multicollinearity. *Internal consistency reliability* corresponds to measurement items' uniformity or the degree of measurement items' collective measurement capability of the same variable (Henson, 2001: 177). Convergent validity, on the other hand, expresses the fact that alternative measurements made with the measurement tool are positively related to each other. Fornell and Larcker's (1981) AVE (Average Variance Extracted) method may be used for measurement tools' convergent validity. The AVE corresponds to a coefficient between 0 and 1, and a value of at least 0.50 is highly recommended for research models' variables (Fornell & Larcker, 1981: 45–46). For the data collection tool's internal reliability and convergent validity, the PLS algorithm was run on the data obtained from 42 items, and the findings shown in Table 3 were reached.

**Table 3.** Findings of Internal Consistency and Convergent Validity

| Dimension* | CA | CR | rho _A | AVE |
|---|---|---|---|---|
| AR | 0.826 | 0.885 | 0.851 | 0.661 |
| BİL | 0.920 | 0.940 | 0.920 | 0.758 |
| ESA | 0.613 | 0.720 | 0.835 | ***0.473*** |
| FRK | 0.727 | 0.828 | 0.753 | 0.548 |
| KK | 0.851 | 0.894 | 0.860 | 0.628 |
| PEB | 0.908 | 0.936 | 0.910 | 0.785 |
| SE | 0.765 | 0.851 | 0.808 | 0.593 |
| YTB | 0.922 | 0.945 | 0.928 | 0.811 |
| YÖN | 0.926 | 0.948 | 0.929 | 0.822 |
| ÇB | 0.890 | 0.924 | 0.891 | 0.753 |

AR=Perceived Risk, BİL = Computer Self-Efficacy, ESA=Legacy System Habit, FRK=Awareness, KK=Facilitating Conditions, PEB=Performance Expectancy, SE=Social Influence, YTB=Intention to Invest, YÖN= Intention of Use in Foreign Payments, ÇB=Effort Expectancy

The first three columns of Table 3 (CA, CR, and rho_A) present the coefficients related to the internal consistency of the measurement model. As seen in Table 3, all variables of the measurement model indicated CA[1] values of 0.60 or above. Deemed acceptable values were also calculated for CR[2] and rho_a, and all findings indicated that the measurement model was proper in terms of internal consistency.

The measurement model was also examined within the scope of convergent validity, and the AVE values in Table 3 and the outer loadings are indicators in this regard. Convergent validity demonstrates that alternative measurements made with one construct are positively related. Indicators (items) of the variables should cause a significant variation (variance) in the relevant variable. According to AVE findings in Table 3, all variables except ESA (Legacy System Habit) have values of 0.50 and above. In this context, reviewing the items in the ESA dimension should be helpful. The outer loadings of all 42 items were also examined for convergent validity. Outer loading is the contribution of an item to the variance of its assigned variable. A value of 0.70 and above demonstrates that the item is appropriate for the relevant variable. In the measurement model, items with an outer loading below 0.40 should be excluded. For outer loadings between 0.40 and 0.70, it can be decided according to the change in the reliability of the structures. Suppose an increase in the reliability of the variable is observed when an item with a value in this range is removed. In that case, the relevant item can be excluded from the measurement model (Hair et al., 2017: 114). On the subject, Hulland (1999) suggested 0.50 as the lowest limit for outer loadings (Hulland, 1999: 198). The value of 0.60 was accepted as the limit in this research, and items with a loading value below 0.60 were excluded from the measurement model. The items excluded from the measurement model are ESA1, ESA2, and SE4.

Along with the analysis of internal reliability and convergent validity, the measurement model was also examined regarding multicollinearity, which is an issue that arises when the data collection tool's items are highly correlated with each other. In this case, it becomes uncertain about examining the effects of the items and variables on the phenomenon to be measured (Kock, 2015: 7). The items' variance inflation factors (VIF) can be used to examine the issue. Survey items with a VIF value greater than five are considered to have multicollinearity (Hair et al., 2017: 194). Firstly, VIF values of the 39-item measurement model, which excluded three items that had indicated outer loadings lower than 0.60, were examined. It was seen that YÖN1 (6.54), YÖN2 (9.00), and YÖN3 (5.02) had VIF values greater than 5. At this point, YÖN2, which presented the highest VIF value (9.00), was excluded from the model. When the VIF values of 38 items were recalculated, YÖN1 and YÖN3 were found to reach appropriate values (YÖN1=3.46; YÖN3=3.92).

The measurement model, which was reduced to 38 propositions in its final form, was also examined in terms of discriminant validity. Regarding discriminant validity, a variable should have the strongest relationship with its items (Hubley, 2014: 1664). The Heterotrait-Monotrait Ratio (HTMT) developed by Henseler et al. (2015) was used while examining the discriminant validity of the measurement model. According to this method, the mutual HTMT ratios of the variables should be below 90% (0.90). As seen in Table 4, HTMT ratios below 0.90 were calculated among all variables in the measurement model:

[1] CA (Cronbach's Alpha) represents the consistent contribution ratio of a set of measurement items to variance. The CA corresponds to a coefficient between 0 and 1. In general, 0.65 and above are considered adequate (Vaske et al., 2017: 165).

[2] CR (Composite Reliability) takes a value between 0 and 1, similar to CA. CR values between 0.60 and 0.70 indicate an acceptable level, while 0.70 and 0.90 indicate a more favorable level. However, CR values of more than 0.95 are not recommended because they demonstrate that the measurement items measure the same phenomenon and are not a valid criterion of the variable to which they belong (Hair et al., 2017: 112).

**Table 4.** HTMT Findings of the Measurement Model

| | AR | BİL | ESA | FRK | KK | PEB | SE | YTB | YÖN | ÇB |
|---|---|---|---|---|---|---|---|---|---|---|
| **AR** | | | | | | | | | | |
| **BİL** | 0.044 | | | | | | | | | |
| **ESA** | 0.579 | 0.174 | | | | | | | | |
| **FRK** | 0.302 | 0.454 | 0.460 | | | | | | | |
| **KK** | 0.101 | 0.481 | 0.322 | 0.796 | | | | | | |
| **PEB** | 0.271 | 0.420 | 0.463 | 0.862 | 0.774 | | | | | |
| **SE** | 0.165 | 0.266 | 0.287 | 0.699 | 0.740 | 0.690 | | | | |
| **YTB** | 0.321 | 0.266 | 0.416 | 0.787 | 0.636 | 0.786 | 0.730 | | | |
| **YÖN** | 0.262 | 0.335 | 0.342 | 0.649 | 0.594 | 0.692 | 0.668 | 0.793 | | |
| **ÇB** | 0.153 | 0.524 | 0.329 | 0.781 | 0.887 | 0.807 | 0.590 | 0.641 | 0.597 | |

Along with the assessments above, the measurement model consisting of 38 propositions was also re-examined within the scope of internal consistency and convergent validity, and it was verified that there were adequate findings for each indicator. The results in Table 5 reveal the validity and reliability of the final measurement model.

**Table 5.** Findings of Internal Consistency and Convergent Validity of the Final Measurement Model

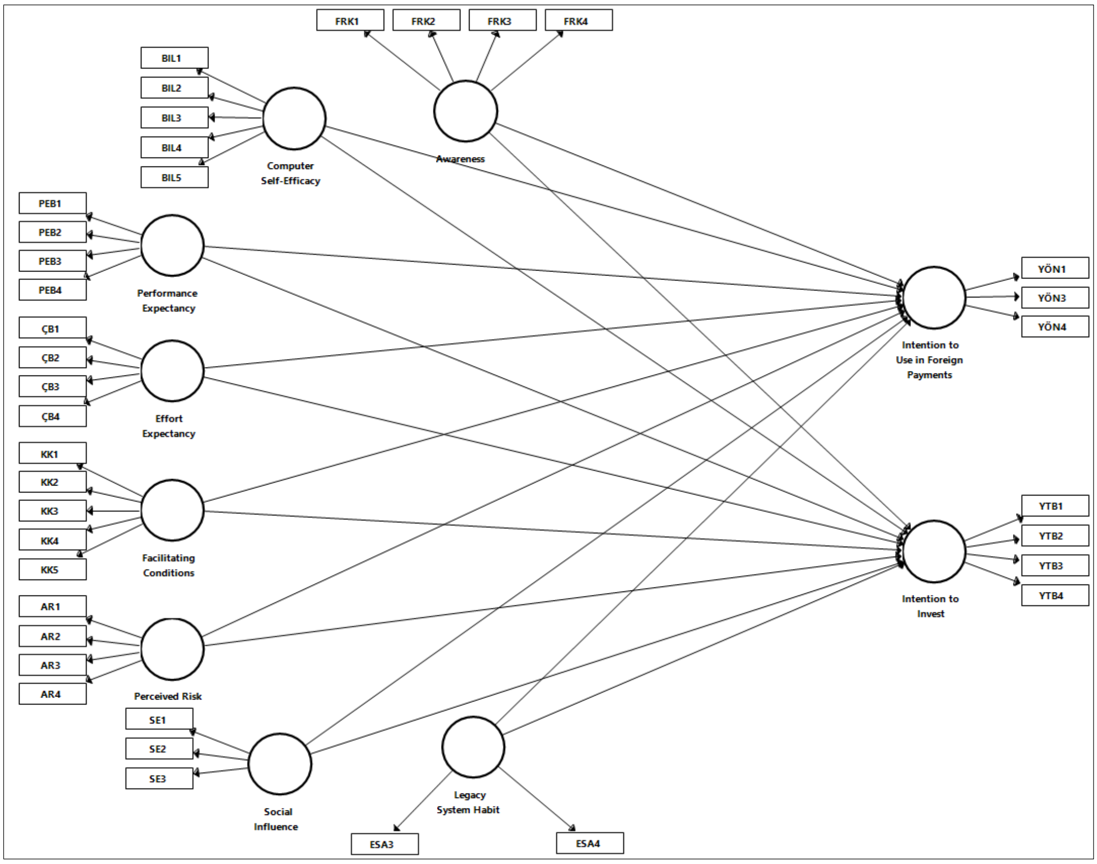
| | AR | BİL | ESA | FRK | KK | PEB | SE | YTB | YÖN | ÇB |
|---|---|---|---|---|---|---|---|---|---|---|
| **CA** | 0.826 | 0.920 | 0.824 | 0.727 | 0.851 | 0.908 | 0.798 | 0.922 | 0.875 | 0.890 |
| **rho _A** | 0.850 | 0.921 | 1,000 | 0.753 | 0.860 | 0.910 | 0.819 | 0.928 | 0.881 | 0.891 |
| **CR** | 0.885 | 0.940 | 0.914 | 0.828 | 0.894 | 0.936 | 0.881 | 0.945 | 0.923 | 0.924 |
| **AVE** | 0.661 | 0.758 | 0.842 | 0.548 | 0.628 | 0.785 | 0.712 | 0.811 | 0.801 | 0.753 |

| | AR | BİL | ESA | FRK | KK | PEB | SE | YTB | YÖN | ÇB |
|---|---|---|---|---|---|---|---|---|---|---|
| AR1 | 0.842 | | | | | | | | | |
| AR2 | 0.883 | | | | | | | | | |
| AR3 | 0.842 | | | | | | | | | |
| AR4 | 0.669 | | | | | | | | | |
| BİL1 | | 0.823 | | | | | | | | |
| BİL2 | | 0.829 | | | | | | | | |
| BİL3 | | 0.895 | | | | | | | | |
| BİL4 | | 0.910 | | | | | | | | |
| BİL5 | | 0.891 | | | | | | | | |
| ESA3 | | | 0.874 | | | | | | | |
| ESA4 | | | 0.959 | | | | | | | |
| FRK1 | | | | 0.657 | | | | | | |
| FRK2 | | | | 0.696 | | | | | | |
| FRK3 | | | | 0.837 | | | | | | |
| FRK4 | | | | 0.758 | | | | | | |
| KK1 | | | | | 0.793 | | | | | |
| KK2 | | | | | 0.821 | | | | | |
| KK3 | | | | | 0.809 | | | | | |
| KK4 | | | | | 0.845 | | | | | |
| KK5 | | | | | 0.684 | | | | | |
| PEB1 | | | | | | 0.868 | | | | |
| PEB2 | | | | | | 0.920 | | | | |
| PEB3 | | | | | | 0.903 | | | | |
| PEB4 | | | | | | 0.851 | | | | |

| | | | | |
|---|---|---|---|---|
| SE1 | 0.781 | | | |
| SE2 | 0.886 | | | |
| SE3 | 0.860 | | | |
| YTB1 | | 0.924 | | |
| YTB2 | | 0.894 | | |
| YTB3 | | 0.931 | | |
| YTB4 | | 0.851 | | |
| YÖN1 | | | 0.899 | |
| YÖN3 | | | 0.933 | |
| YÖN4 | | | 0.851 | |
| ÇB1 | | | | 0.871 |
| ÇB2 | | | | 0.846 |
| ÇB3 | | | | 0.894 |
| ÇB4 | | | | 0.860 |

After examining the measurement model, the structural model was analyzed to obtain the findings within the scope of the research aim. Along with the PLS-SEM algorithm, the bootstrapping technique was used to determine whether the findings were statistically significant. In bootstrapping, a large sample group is created, and the variability of the findings is analyzed (Streukens & Leroi-Werelds, 2016: 619). There are statistically various criteria and settings for the bootstrapping technique. Within the scope of the research, settings such as a 5,000-sample size, full bootstrapping, BCa bootstrapping (bias-corrected and accelerated), and two-tailed testing were used as suggested by Hair et al. (2017: 175-177). Figure 1 shows the coefficients of determination ($R^2$) and other findings obtained by bootstrapping:

**Figure 1.** Structural Model of the Research



In analyzing the structural model, the coefficients of determination ($R^2$) observed in the dependent variables (YÖN and YTB) were examined first. The independent variables of the model have an explanatory power of 51% ($R^2$=0.510; p=0.00) on YÖN (Intention to Use in Foreign Payments) and 63% (0.630, p=0.00) on YTB (Intention to Invest). These findings showed that the explanatory power of the model is moderate. Relevant *p* values below 0.05 indicate that the change in dependent variables is statistically significant.

Within the scope of the research aim, the interaction between the variables of the research model was analyzed with three coefficients. These are the path coefficients (β), $f^2$ effect sizes, and predictive relevance ($q^2$) effect sizes, respectively. While the PLS algorithm calculated the path coefficients and $f^2$ values, the blindfolding technique was used to obtain data on the predictive relevance of the research model and its variables. The findings of path coefficients (β) and $f^2$ effect sizes as indicators of the interaction between the variables are shown in Table 6.

**Table 6.** Path Coefficients (β) and $f^2$ Effect Sizes of Independent Variables

| | (β) | t | p** | | $f^2$* | t | p** |
|---|---|---|---|---|---|---|---|
| **AR - > YTB** | **-0.089** | **2,393** | **0.017** | AR - > YTB | 0.015 | 1.125 | 0.261 |
| **AR - > YÖN** | **-0.100** | **2,064** | **0.039** | AR - > YÖN | 0.015 | 0.936 | 0.349 |
| BİL - > YTB | -0.055 | 1,783 | 0.075 | BİL - > YTB | 0.006 | 0.855 | 0.393 |
| BİL - > YÖN | 0.066 | 1,822 | 0.068 | BİL - > YÖN | 0.007 | 0.831 | 0.406 |
| ESA - > YTB | -0.035 | 0.902 | 0.367 | ESA - > YTB | 0.002 | 0.354 | 0.723 |
| ESA - > YÖN | 0.005 | 0.120 | 0.905 | ESA - > YÖN | 0.000 | 0.010 | 0.992 |
| **FRK - > YTB** | **0.218** | **4.361** | **0.000** | **FRK - > YTB** | **0.055** | **2.167** | **0.030** |
| FRK - > YÖN | 0.094 | 1,716 | 0.086 | FRK - > YÖN | 0.008 | 0.771 | 0.441 |
| KK - > YTB | -0.036 | 0.703 | 0.482 | KK - > YTB | 0.001 | 0.257 | 0.797 |
| KK - > YÖN | 0.001 | 0.008 | 0.994 | KK - > YÖN | 0.000 | 0.000 | 1,000 |
| **PEB - > YTB** | **0.349** | **6.208** | **0.000** | **PEB - > YTB** | **0.103** | **2,934** | **0.003** |
| **PEB - > YÖN** | **0.296** | **5,000** | **0.000** | **PEB - > YÖN** | **0.056** | **2.326** | **0.020** |
| **SE - > YTB** | **0.282** | **6,555** | **0.000** | **SE - > YTB** | **0.116** | **3.179** | **0.001** |
| **SE - > YÖN** | **0.283** | **6.091** | **0.000** | **SE - > YÖN** | **0.088** | **2,896** | **0.004** |
| ÇB - > YTB | 0.081 | 1.657 | 0.098 | ÇB - > YTB | 0.005 | 0.763 | 0.445 |
| ÇB - > YÖN | 0.097 | 1,533 | 0.125 | ÇB - > YÖN | 0.006 | 0.710 | 0.478 |

* $f^2$: $R^2$ included – $R^2$ excluded / 1 –$R^2$ included
** p<0.05

The path coefficients (β) indicating the interaction in the research model are located in the left part of Table 6. The path coefficient is an indicator that determines the direction and level of interaction between dependent and independent variables. Path coefficients get values between -1 and 1, and coefficients close to 1 indicate a positive and strong interaction, while a coefficient close to -1 represents a negative and strong interaction. When the coefficient closes to 0, the relevant interaction gets weaker (Hair et al., 2017: 195–197). The findings shown in bold in Table 6 belong to the independent variables with a significant (p<0.05) effect on the dependent variables.

As seen in Table 6, PEB (Performance Expectancy) demonstrated the highest path coefficients in the interaction between the dependent variables (YTB=0.349; YÖN=0.296; p=0.00). In terms of the research model, *performance expectancy* can be defined as the level of perception that the efficiency of financial transactions will increase with the use of crypto assets. The performance expectancy of the participants for the functions of crypto-assets moderately and positively affects their intention to use crypto assets in foreign payments (YÖN) and invest in crypto-assets (YTB). On the other hand, SE (Social Influence) was determined to be another variable that had a statistically significant effect on the dependent variables of the research model. Path coefficients were calculated at 0.282 in the interaction between SE and YTB and at 0.283 in the interaction between SE and YÖN (p=0.00). *Social influence* corresponds to guiding the individual to use the relevant technology product by the social environment. As the participants' perceptions of social influence increase, their intention to use crypto assets in foreign payments and investments is also positively affected. However, according to the calculated path coefficients, the interaction level is moderate for both dependent variables.

Table 6 shows a significant path coefficient (β=0.218; p=0.00) between FRK (Awareness) and YTB. On the contrary, it was found that the interaction between FRK and YÖN was not significant (p>0.05). Awareness of the participants towards crypto assets affects their intention to invest in crypto assets positively and at a low level. According to path coefficients, it was found that AR (Perceived Risk) also had significant effects on dependent variables. The path coefficients were calculated between AR and YÖN at -0.100 (p=0.039), and AR and YTB at -0.089 (p=0.017). *Perceived risk,* which defines the individual perception of the risk factors that crypto assets carry, negatively affects the participants' intention to use crypto assets in foreign payments and investments. However, β coefficients indicated a weak interaction level.

In the analysis of the research model, the $f^2$ effect sizes and alternate indicators of the interaction between the variables were also examined. Effect size is a coefficient ranging between 0.02 and 0.35, and 0.02 corresponds to weak influence, while 0.35 to strong influence (Kwong & Wong, 2013: 26). According to the $f^2$ findings in the right part of Table 6, PEB and SE demonstrated a significant effect on YÖN, while PEB, SE, and FRK significantly affected YTB. The $f^2$ effect sizes were 0.088 (p=0.004) between SE and YÖN and 0.116 (p=0.001) between SE and YTB. In this context, it can be mentioned that there is a medium level of interaction in terms of YTB and a low level of interaction in terms of YÖN. On the other hand, the $f^2$ effect sizes were calculated as 0.056 (p=0.02) between PEB and YÖN and 0.103 (p=0.003) between PEB and YTB, and these findings corresponded to weak and medium effects, similar to SE. FRK was found to have a significant effect only on YTB, but the $f^2$ coefficient calculated as 0.055 indicated a low-level effect. Findings of the $f^2$ effect sizes revealed that SE was the variable with the strongest effect on both dependent variables.

The findings regarding the $f^2$ values contain differences according to the path coefficients. While AR affected the dependent structures of the structural model (YÖN and YTB) significantly and negatively according to the path coefficients, it was observed that there was no significant interaction in terms of $f^2$ coefficients (p<0.05). In addition, according to path coefficients, the variable with the highest effect on both dependent variables was PEB. However, regarding the $f^2$ effect sizes, it was determined that the most effective variable was SE. Considering the path and $f^2$ findings, it can be stated that PEB and SE are crucial variables for the research model.

In structural equation modeling analysis, predictive relevance can also be used to examine the interaction between variables. The blindfolding technique was used to examine the research model's predictive relevance and determine the contribution levels of independent variables. In this method, $Q^2$ values are first calculated based on estimating the change in the dependent variables. $Q^2$ values of 0.395 for YÖN and 0.503 for YTB were obtained. $Q^2$ is a coefficient corresponding to the explanation rate in the dependent variables. Regarding the obtained $Q^2$ values, it can be stated that the model's predictive relevance is moderate. On the other hand, in line with the recommendation of Hair et al. (2017), the $q^2$ effect sizes, which demonstrate how independent variables contribute to the $Q^2$, were also calculated. The $q^2$ values for the independent variables were obtained with the formula "$q^2$= $Q^2$ included - $Q^2$ excluded / 1 - $Q^2$ included". 0.02 indicates a weak, 0.015 a moderate, and 0.035 a strong predictive relevance (Hair et al., 2017: 207–208). The $q^2$ effect sizes revealing the predictive relevance of the independent variables are shown in Table 7:

**Table 7.** Findings of Predictive Relevance Effect Sizes ($q^2$)

| **Variables** | **$q^2$*** | **Variables** | **$q^2$*** |
|---|---|---|---|
| AR - > YTB | 0.008 | KK - > YÖN | 0.002 |
| AR - > YÖN | 0.008 | KK - > YTB | 0,000 |
| BİL - > YTB | 0.002 | PEB - > YÖN | **0.04** |
| BİL - > YÖN | 0.005 | PEB - > YTB | **0.06** |
| ESA - > YTB | 0,000 | SE - > YÖN | **0.06** |
| ESA - > YÖN | -0.002 | SE - > YTB | **0.07** |
| FRK - > YTB | **0.032** | ÇB - > YÖN | 0.003 |
| FRK - > YÖN | 0.003 | ÇB - > YTB | 0.002 |

*$q^2$: $Q^2$ included – $Q^2$ excluded / 1 – $Q^2$ included

Table 7 demonstrates that five independent variables' $q^2$ effect sizes are higher than 0.02. According to the calculated $q^2$ values, the variables can be ranked as SE ($q^2$=0.06) and PEB ($q^2$=0.04) for YÖN and SE ($q^2$=0.07), PEB ($q^2$=0.06) and FRK ($q^2$=0.032) for YTB. In this context, findings parallel to the results regarding the effect size ($f^2$) were obtained, and it was seen that SE was the prominent variable in terms of both dependent structures. In addition, PEB, which was determined to be the most effective variable according to the path coefficients, had satisfactory predictive power on dependent variables, even though it lags the SE.

## 6. DISCUSSION

Crypto assets, which function independently of the current financial system, cause many discussions due to the threats and opportunities they carry. The most fundamental characteristic of crypto assets that distinguishes them from other financial instruments, such as national currency, stocks, and gold, is that they are built on the blockchain. The fact that crypto assets allow transactions between parties without the need for the approval or supervision of a third party makes it challenging to apply the provisions of the legislation in terms of legality and taxation. Although official institutions' inspection and surveillance activities are restricted due to their decentralized network trading, crypto assets are still widely accepted as investment instruments. The widespread acceptance of crypto assets raises many research questions, particularly on what factors influence individuals' adoption of crypto assets.

There may be differences or distinctions between crypto assets regarding their software features. However, in terms of their financial characteristics, the two main functions of payment and investment stand out for crypto assets. These functions can also be defined as the usage purposes of crypto assets by individuals or institutions. The aim of this research is to examine the factors affecting the use of crypto assets in line with these functions. As a result of the literature review, a research model and data collection tool were developed on the axis of UTAUT-2, and data analysis was carried out through PLS-SEM modeling. In the research model, eight independent variables were adopted in light of other reviewed studies. On the other hand, two different dependent variables were assigned to the model. The first is called the intention to use in foreign payments. The relevant dependent variable was included in the model, considering that crypto assets could be efficient alternatives for payments, especially for foreign remittances, due to their transaction time and fee advantages. The second dependent variable corresponded to the other usage area of crypto assets and was included in the research model under "intention to invest." The effects of independent variables were examined by path coefficients (β), $f^2$ effect sizes, and $q^2$ effect sizes. The findings of path coefficients were also compared and discussed below with the studies examined in Table 2 as well as with other studies in the literature.

Path coefficients demonstrated that performance expectancy (β=0.296), social influence (β=0.283), and perceived risk (β =-0.100) significantly affected the "intention to use in foreign payments," respectively. For "intention to invest," it was determined in order of importance that performance expectancy (β=0.349), social influence (β=0.282), awareness (β=0.218), and perceived risk (β= -0.089) had significant effects. As seen from the findings, PEB (Performance Expectancy) demonstrated the highest path coefficients in the interaction between both dependent variables. Compared to the studies analyzed in Table 2, Arias Oliva et al. (2019) also observed that performance expectancy had the most effect on the intention to use Bitcoin (β=0.764, p<0.001). While Gillies et al. (2020) found that there was no significant interaction between performance expectancy and the intention to use Bitcoin (Gillies et al., 2020: 35), in the research where the UTAUT-2 model was developed, performance expectancy on behavioral intention had a positive effect (β=0.210, p<0.001) (Venkatesh et al., 2012: 170). Findings on PEB are also compatible with other studies in the literature. Thus, Ter Ji-Xi et al. (2021) have found that the performance expectancy was the most critical driver for the intention to use cryptocurrency, and Li et al. (2023) have observed a significant and positive interaction between the relevant variables. In this respect, it can be stated that findings related to performance expectancy are compatible with other studies.

Social influence (SE) was the second-ranking construct in the context of its significant impact on the dependent variables. From the reviewed studies in Table 2, Gillies et al. (2020: 35) also found a positive and low level of interaction between social influence and the intention to use Bitcoin (β= 0.263; p=0.00). Similarly, in the study in which the UTAUT-2 model was developed, it was observed that there was a low level (β= 0.140; p=<0.05) and positive interaction between social influence and behavioral intention (Venkatesh et al., 2012: 169). While Arias-Oliva et al. (2019: 9) and other studies in the literature (Ter Ji-Xi et al., 2021; Li et al., 2023) have found that social influence had no significant impact on the intention to use, Yeong et al. (2022) have determined a weak and significant interaction for social influence (Yeong et al., 2022: 9). The findings regarding social influence vary in the literature, and one could state that the importance of social influence may depend on the demographic characteristics of the studies' sample group. Thus, the fact that the studies with significant findings were conducted in Malaysia (Yeong et al., 2022), Hong Kong (Venkatesh et al., 2012), and Türkiye (this study) reveals the importance of examining the impact of social influence on the acceptance of new technologies in the context of different countries or cultures. The results of survey-based research by ING Bank in 2018 also reveal crucial findings on the subject. Individuals from 15 different countries participated in the survey, and it was found that the highest percentage of those who saw Bitcoin as the future of spending online (53%) and the future of investment (49%) was Türkiye. In contrast, the lowest percentages (16% and 12%) belonged to individuals from Luxembourg (ING, 2018: 12). These findings demonstrate that many characteristics, such as income level, education, country, and culture, may be essential for attitudes towards crypto assets and expose that social influence may also differ across countries. Thus, in the research of ING Bank, the attitudes of participants from Türkiye towards Bitcoin may have been positively affected by the support from their social environment. Therefore, examining the factors affecting social influence in the context of acceptance of new technologies could be beneficial, and future studies could consider this subject in a detailed way.

Findings demonstrated a significant and low-level path coefficient between FRK (Awareness) and YTB (Intention to Invest). Also, it was found that the interaction between FRK and YÖN was not significant ($p<0.05$). The awareness was included in the research model based on the study of Shahzad et al. (2018), one of the reviewed studies in Table 2. As a matter of fact, in the related study, it was determined that there was a positive ($\beta$ =0.229; p=<0.001) interaction between awareness and the intention to use Bitcoin (Shahzad et al., 2018: 37). In terms of the study, awareness can be defined as an individual perception of his or her level of knowledge about the essential characteristics of crypto assets. Individual perception of knowing the fundamental characteristics of crypto assets were found to be a factor affecting the tendency to invest in crypto assets. Crypto assets are risky investment instruments, and transactions with crypto assets require dissimilar practices and processes compared to other instruments. Therefore, it can be stated that individuals who consider themselves sufficient in these issues are more inclined to invest in crypto assets.

According to the findings, AR (Perceived Risk) was one of the significant determinants of dependent variables. AR can be defined as the perception of the risk factors that crypto assets carry, and it negatively and weakly affected the participants' intention to use crypto assets in foreign payments ($\beta$=-0.100) and intention to invest ($\beta$=-0,089). The basis for adding AR to the research model is the study of Arias-Oliva et al. (2019), which has been reviewed in Table 2. In the related study, it was determined that there was no significant interaction between perceived risk and intention to use (Arias-Oliva et al., 2019: 9). On the other hand, in the study of Li et al. (2023), a significant and negative interaction between perceived risk and intention to use was observed (Li et al., 2023: 11), while other studies in the literature have shown no significant findings for perceived risk (Jariyapan et al., 2022; Namahoot & Rattanawiboonsom, 2022). Similarly, with social influence, it can be stated that findings for perceived risk in the literature vary. Therefore, differences in demographic characteristics of participants like country, culture, and income level may lay behind the different results for perceived risk. For instance, a low-income individual may consider crypto assets risky for use as payment or investment instruments because of his/her sensibility to the possibility of financial losses. In this context, risk perception draws attention as another crucial construct for more detailed examination, and future studies may consider this subject.

Along with path coefficients, independent variables' $f^2$ effect sizes were also analyzed to examine the research model. It was found that social influence ($f^2$= 0.088) and performance expectancy ($f^2$= 0.056) were significantly effective for "intention to use in foreign payments," and social influence ($f^2$= 0.116), performance expectancy ($f^2$=0.103) and awareness ($f^2$=0.055) were significantly effective for "intention to invest." The $q^2$ effect sizes of the variables were also examined, and findings identical to the $f^2$ values were obtained.

When the findings of the study, which were also compatible with other studies in the literature, are taken as a whole, performance expectancy and social influence can be assessed as crucial factors in crypto-asset adoption. Individuals' expectations that crypto assets will provide financial efficiency and the optimistic perspectives of their social environment towards crypto assets become essential in their tendency to use crypto assets as payment and investment instruments. Regarding performance expectancy, it can be said that fast and low-cost transactions play a critical role in accepting crypto assets. Individuals may prefer to use crypto assets if they find them advantageous over other alternative instruments in terms of transaction time and cost. Regarding social influence, the support from value-given persons in accepting a new technology product emerges as an essential factor. The fact that valued individuals in the social environment consider crypto assets positively, use them, and encourage others to do so may positively affect the individual's tendency to use crypto assets.

The study is based on two diverse usage areas of crypto assets as payment and investment instruments. It is thought that such an approach provides more accurate and considerable findings for studies examining individual attitudes toward crypto assets. When the literature was examined, it was observed that other studies on attitudes toward crypto assets generally didn't take this distinction into account. However, using crypto assets or any digital asset as a means of payment or investment are actions that have different purposes and outcomes. Thus, in research on an innovative product or service that offers financial functions, such as crypto assets, it would be beneficial to consider all usage areas of these products or services.

In the scope of the study, recommendations for future studies were also devised. As mentioned above, the impact of social influence and perceived risk on crypto asset adoption varies in the literature, and future studies may consider which factors (e.g., demographic characteristics) play significant roles or moderator effects in social influence and perceived risk in terms of intention to use crypto assets. On the other hand, the YÖN variable of the research model included data collection items regarding international shopping orders. Therefore, it can be stated that the related variable is associated with foreign trade. Crypto assets have transaction time and fee advantages, revealing that they may be efficient alternatives for international payments. In a future study, by adopting a qualitative research method, examining the opportunities and threats of crypto assets in foreign trade payments, and evaluating the opinions of sectoral representatives in this direction would be beneficial. Another study may analyze the possible and current integration between crypto asset systems and international banking, and useful findings can be obtained in terms of contributing to literature and practice.

The basis of the research model and data collection tool was the UTAUT-2, a widely accepted model in the literature. UTAUT-2 is an essential reference for studies on new technology products and services. However, developing a measurement tool compatible with crypto assets' technical features and functions may contribute to the literature. In a future study, a new data collection tool appropriate for the characteristics of crypto assets can be developed.

## 7. CONCLUSIONS

The current study demonstrated that performance expectancy and social influence were crucial factors affecting the intention to use crypto assets as foreign payment and investment instruments. Moreover, awareness was observed as a significant predictor of intention to invest in crypto assets, while perceived risk was effective on both intentions to invest in crypto assets and use crypto assets in foreign payments. Social influence and perceived risk were statistically significant structures to examine in detail, and recommendations were identified in this context. Overall, the study confirmed the crucial factors for the intention to use crypto assets in line with their two main financial functions. Considering that crypto assets are technology products with ongoing development processes, the findings obtained from the study are thought to contribute to future research and applications.

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**Annex:** The English Equivalent of the Data Collection Tool

| Construct | Item | # |
|---|---|---|
| **Awareness** | I know that cryptocurrencies are alternative currencies and payment instruments. | 1 |
| | I know about the advantages and risks of cryptocurrencies. | 2 |
| | I follow cryptocurrency markets. | 3 |
| | I would like to participate in educational programs on cryptocurrencies. | 4 |
| **Computer Self-Efficacy** | When I have an issue with my computer, I usually solve it on my own. | 5 |
| | If I make enough effort, I can easily learn how to use most computer programs. | 6 |
| | I am self-sufficient when it comes to doing things on the computer. | 7 |
| | I can stay calm when I encounter a problem in computer, because I am confident in my abilities. | 8 |
| | I can describe myself as a "computer savvy person". | 9 |
| **Performance Expectancy** | Using cryptocurrency, I can transfer money wherever and whenever I want. | 10 |
| | By using cryptocurrency, I can save time in my payment transactions. | 11 |
| | By using cryptocurrency technology, I can easily control my money online. | 12 |
| | I find cryptocurrency technology useful for my financial transactions. | 13 |
| **Effort Expectancy** | I can easily learn how to use cryptocurrencies. | 14 |
| | I find cryptocurrencies easy to use. | 15 |
| | Making transactions with cryptocurrencies is not difficult for me. | 16 |
| | I can master the use of cryptocurrencies. | 17 |
| **Facilitating Conditions** | I have the necessary resources to use cryptocurrency. | 18 |
| | I have the knowledge necessary to use cryptocurrency. | 19 |
| | It is easy to access the necessary information about using cryptocurrency. | 20 |
| | Cryptocurrencies are compatible with other technology products I use. | 21 |
| | If I have difficulties with my cryptocurrency transactions, I can get help from others. | 22 |
| **Perceived Risk** | Using cryptocurrencies is risky. | 23 |
| | There is a lot of uncertainty around the use of cryptocurrencies. | 24 |
| | Compared to other payment systems and investment instruments, cryptocurrencies are riskier. | 25 |
| | I don't think that cryptocurrency markets are adequately protected against cyber-attacks. | 26 |
| **Social Influence** | I think most of my friends make transactions with cryptocurrencies. | 27 |
| | People whose opinions I value support cryptocurrency technology. | 28 |
| | My acquaintances who trade in cryptocurrencies have a high profile. | 29 |
| **Legacy System Habit** | I am hesitant about emerging payment technologies | 30 |
| | I am hesitant about innovative financial instruments such as cryptocurrencies. | 31 |
| **Intention to Use in Foreign Payments** | When ordering goods from abroad, I may prefer to pay with cryptocurrency. | 32 |
| | I may prefer to use cryptocurrency to send money abroad. | 33 |
| | I predict that I will use cryptocurrencies frequently in the future when making payments abroad. | 34 |
| **Intention to Invest** | I plan to invest by buying cryptocurrencies. | 35 |
| | For me, cryptocurrencies are a more profitable option than other investment instruments. | 36 |
| | I have a positive attitude towards investing in cryptocurrencies. | 37 |
| | I predict that I will use cryptocurrencies as a means of savings in the future. | 38 |