“Demystifying crypto-asset adoption intention: What matters more, technology or human motivation?”

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DEMYSTIFYING CRYPTO-ASSET ADOPTION INTENTION: WHAT MATTERS MORE, TECHNOLOGY OR HUMAN MOTIVATION?

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Abstract

Crypto-assets attract interest as alternatives to centralized financial systems, yet adoption remains limited in advanced economies. This study explores how technological characteristics and human motivations affect adoption intentions, using Czechia as the context of a developed economy. The study applies a dual-stage framework- partial least squares structural equation modelling (PLS-SEM) to test hypotheses on data from 387 Czech adults via face-to-face questionnaires (March-October 2023), and artificial neural network (ANN) analysis to rank factor importance. PLS-SEM findings show Effort Expectancy as the strongest predictor of adoption intention, while Compatibility drives Performance Expectancy, which indirectly drives adoption intention. Relative Advantage significantly shapes Effort Expectancy and indirectly affects adoption intention. However, ANN sensitivity analysis shows technological characteristics dominate overall, with Compatibility showing the highest normalized importance (91.5%), followed by Relative Advantage (79.9%) and Effort Expectancy (50.9%). These results show technological characteristics and human motivations both contribute to adoption intentions, with prominence depending on analytical perspective- ease of use was the strongest direct predictor in PLS-SEM, while Compatibility dominated overall predictive importance in ANN. This indicates that in a stable, resilient financial environment, digital proficiency does not translate into tolerance for complexity; rather, adoption intentions depend on the technology's ability to align effortlessly with established daily habits. Consequently, the study suggests fostering adoption in developed economies requires reducing structural complexity rather than merely increasing digital literacy.

Keywords crypto-assets, adoption intentions, compatibility, relative advantage, performance expectancy, effort expectancy, UTAUT2, innovation diffusion theory, Artificial Neural Network

JEL Classification E42, O33, G41

INTRODUCTION

In the current era of rapid digitalization, the global financial landscape is undergoing a profound transformation (Hlawiczka & Mikustak, 2026). This shift is largely driven by the systemic vulnerabilities of centralized frameworks – marked by institutional corruption, lack of transparency, and susceptibility to human manipulation – which were critically exposed during the 2008 financial crisis and the COVID-19 pandemic (Bahoo, 2020; Mirzaei, 2019). The emergence of crypto-assets – a broad category encompassing cryptocurrencies, tokens, and other digital assets built on decentralized ledger technology – represents one of the most significant shifts in how value is stored and transferred. Although related concepts such as blockchain technology and decentralized finance (DeFi) form part of this broader ecosystem, this study focuses specifically on crypto-assets as a distinct construct, independent of the underlying technological infrastructure or specific financial function. Unlike traditional financial systems that rely on

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centralized intermediaries, crypto-assets offer the promise of transparency, lower transaction costs, and a hedge against the vulnerabilities of institutional corruption or systemic failures. However, despite the technical maturity of these instruments and the growing infrastructure surrounding them, their widespread adoption into everyday economic activity remains a significant paradox, particularly in developed economies.

The relevance of investigating crypto-asset adoption is underscored by the ongoing debate regarding the future of money and the role of decentralized finance (DeFi) in modern society. While crypto-assets have moved from a niche interest of technology enthusiasts to a subject of serious institutional investment, their transition to a mainstream medium of exchange or a standard investment vehicle for the general public is still incomplete. This stagnation is particularly visible in developed European markets, where established banking systems are efficient, and trust in national institutions is relatively high, yet the potential for digital innovation remains vast.

Czechia ranks 24th in the IMD World Digital Competitiveness Index (IMD, 2023), with internet penetration exceeding 88% (Czech Statistical Office [CZSO], 2025) and near-universal broadband coverage, yet performs at 80.6% of the EU innovation average (European Commission [EC], 2025) and ranks 62nd in the 2025 Global Crypto Adoption Index (Chainalysis, 2025). Despite its advanced digital infrastructure and prominent role in crypto-asset innovation (EC, 2024), institutional trust in the traditional banking sector remains exceptionally resilient, creating a unique context to examine crypto-asset adoption intentions.

The core of the scientific problem lies in the theoretical and empirical ambiguity surrounding the drivers of this adoption. While existing literature has identified various factors influencing technology acceptance, there is a lack of consensus on the hierarchy of these drivers within developed economies. Current scientific discourse reveals a significant gap: it remains unclear whether the primary bottleneck for crypto-asset adoption intention is rooted in technological characteristics – such as compatibility and relative advantage – or in human motivational factors – such as performance and effort expectancy. Most existing studies focus on developing nations with unstable currencies, leaving a "knowledge void" regarding how these factors interact in stable, high-income environments like Czechia. Furthermore, the interplay between purely technical attributes (technology-centric view) and behavioral motivations (user-centric view) has not been sufficiently modelled to explain why adoption remains hesitant despite technological readiness. Addressing this gap is crucial not only for advancing academic theory but also for providing the necessary empirical foundation for understanding the mechanics of digital transformation in the modern financial world.

1. LITERATURE REVIEW

The rapid evolution of the financial landscape, driven by decentralized technologies, has positioned crypto-assets as a significant alternative to traditional systems. Understanding the mechanisms behind their adoption requires a multidimensional perspective that accounts for both technological characteristics and psychological drivers. This study builds upon the synthesis of the Unified Theory of Acceptance and Use of Technology (UTAUT2) and Innovation Diffusion Theory (IDT) to explain adoption intention in a developed economy.

1.1. Crypto adoption

Crypto adoption is defined as the intentional process through which individuals become users of digital assets, integrating and utilizing them within societal structures (Chen et al., 2022; Shahzad et al., 2018). Given the potential benefits and inherent challenges of these assets, academic discourse has extensively examined the determinants of user attitudes (Albayati et al., 2020; Chen et al., 2022). Research highlights the significance of fundamental awareness and technical knowledge (Alomari & Abdullah, 2023; Hua et al., 2019; Shahzad et al., 2018; Easley et al., 2019; Polasik et al., 2015), alongside technological drivers such as performance and effort expectancy (Alomari & Abdullah, 2023; Arias-Oliva et al., 2019; Ter Ji-Xi et al., 2021). Furthermore, adoption is influenced by external factors, including transaction costs, regulatory environments, and the availability of exchange platforms (Borrás & Edler, 2020; Frederiks et al., 2022; Hairudin et al., 2022; Zhao et al., 2024; Li & Wang, 2017). Beyond technical protections and design (Ooi et al., 2021; Albayati et al., 2020), behavior-based attributes – such as technology enthusiasm and payment diversity – as well as perceived innovation characteristics like compatibility and relative advantage, serve as critical influencers (Bharadwaj & Deka, 2021; Frederiks et al., 2022; García-Monleón et al., 2023; Polasik et al., 2015).

The core of this adoption lies in blockchain technology, which offers a transparent and manipulation-resistant alternative to traditional financial limitations (Akyildirim et al., 2020; Hughes et al., 2019; Mendling et al., 2018; Saiedi et al., 2021; Wanner et al., 2022). Despite this potential, the sector remains in its infancy, facing significant hurdles related to hacking risks, fraudulent activities, extreme price volatility, and a lack of consistent government policies (Albayati et al., 2020; Alomari & Abdullah, 2023; Hooda et al., 2022). These complexities are particularly relevant when comparing developed nations with advanced infrastructures to developing economies, as national development factors – including income levels and institutional stability – have been shown to significantly moderate crypto-asset adoption patterns (Bhimani et al., 2022), while human factors like effort and performance expectations remain central to technology acceptance in both contexts (Arts et al., 2011).

While technology adoption has been examined across auxiliary domains such as e-government, mobile banking, and automated systems (Hooda et al., 2022; Çera et al., 2020; Dinh & Park, 2024; Hughes et al., 2019; Rana et al., 2019; Misra et al., 2022; Nordhoff et al., 2020; Venkatesh & Bala, 2008; Wanner et al., 2022; Liang et al., 2021; Venkatesh et al., 2003, 2012; Venkatesh et al. 2016), the present study draws primarily on crypto-asset specific literature. To synthesize these influences, the Unified Theory of Acceptance and Use of Technology (UTAUT) emerged as a comprehensive framework, integrating elements from eight primary models – including TAM and TPB – to explain user behavior (Venkatesh et al., 2003; Lai, 2017). In the field of technology acceptance research, adoption intention has been empirically validated as the primary driver and most significant predictor of actual technology use (Venkatesh et al., 2012). Additionally, Innovation Diffusion Theory (IDT) provides a critical lens for understanding how perceived attributes of an innovation, such as compatibility and relative advantage, determine the rate of adoption (Rogers, 1995; Bharadwaj & Deka, 2021). While models such as fit-viability have been used to explain blockchain adoption in enterprise settings (Liang et al., 2021), there remains a literature gap regarding how individual perceptions of innovative features influence the decision-making process.

1.2. Technological antecedents: Compatibility and relative advantage

Innovation Diffusion Theory (IDT) posits that an individual's perception of a technology's novelty is a fundamental prerequisite for its acceptance. Specifically, IDT identifies compatibility and relative advantage as key perceived attributes that drive the eventual adoption of innovations (Rogers, 1995; Meyer, 2004; Bharadwaj & Deka, 2021). Building on this framework, the present study examines how these innovative characteristics shape individuals' perceptions of crypto-assets – specifically regarding their perceived usefulness (performance expectancy) and ease of use (effort expectancy).

1.2.1. Compatibility, performance, and effort expectancy

Compatibility is defined as the degree to which an individual perceives a new technology as consistent with existing information infrastructure, values, and past experiences (Rogers, 1995; Frederiks et al., 2022). Previous research suggests that innovation factors, including compatibility, significantly drive the intention to invest in crypto-assets and enhance the adoption of innovative features (Arts et al., 2011; Sukumaran et al., 2022). Despite these perspectives, a consensus on the impact of compatibility on crypto-asset adoption remains elusive (Bharadwaj & Deka, 2021). While some researchers identified a noteworthy positive influence, others, such as Frederiks et al. (2022),

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suggested only a minor effect. Furthermore, the literature indicates that compatibility may not influence usage directly but could exert an indirect effect mediated by user perceptions (Kumpajaya & Dhewanto, 2015). Given these conflicting findings, it is imperative to investigate how compatibility shapes adoption through the lenses of perceived usefulness (performance expectancy) and perceived ease of use (effort expectancy) (Bharadwaj & Deka, 2021; Kumpajaya & Dhewanto, 2015). Drawing on the synthesis of IDT and UTAUT2, this paper predicts that individuals who perceive crypto-assets as compatible with their existing practices have an advantage in assessing their utility and are likely to experience greater ease of use.

1.2.2. Relative advantage, performance, and effort expectancy

Innovation adoption positively correlates with an innovation's relative advantage, commonly defined as its perceived superiority over the existing alternative it aims to replace (Rogers, 1995; Sukumaran et al., 2022). However, the strength of this association often pales in comparison to the relationship between compatibility and innovation adoption (Arts et al., 2011). Moreover, the impact of relative advantage on behavior typically outweighs its influence on intention. At the same time, individuals tend to see more advantages in adopting new technology when they already use it than when they only intend to start (Arts et al., 2011). In contrast, Bharadwaj and Deka (2021) and Sukumaran et al. (2022) found no evidence of the relative advantage of adopting crypto in investing. Despite these mixed results, particularly regarding usability, the present study predicts that relative advantage prompts individuals to perceive blockchain-based crypto-assets as both useful and easy to use, thereby indirectly boosting adoption intention.

1.3. Human motivations – performance and effort expectancy

1.3.1. Performance expectancy and crypto adoption

Performance expectancy refers to the extent to which an individual believes that utilizing a particular system or technology would be advantageous for them and has the potential to improve their overall performance in various activities (Bommer et al., 2022; Davis, 1989; Shahzad et al., 2018; Venkatesh et al., 2003, 2012). In other words, it refers to individuals' perception of how much they will benefit from using new technology. Past technology adoption-based research has likewise shown that perceiving new technology as useful has an evident positive effect on individuals' behavioral intention to adopt it in the future. According to various studies, Venkatesh et al. (2003), individuals believe they will benefit from adopting the latest technology. Earlier research on crypto-assets from both the TAM and UTAUT points of view has consistently shown how important performance expectations are in predicting crypto adoption (Arias-Oliva et al., 2019; Bharadwaj & Deka, 2021; Jariyapan et al., 2022; Kumpajaya & Dhewanto, 2015; Nseke, 2018; Ter Ji-Xi et al., 2021; Yeong et al., 2022). Researchers have identified performance expectancy as a highly influential factor in crypto adoption (Bommer et al., 2023). The ability of crypto-assets to accomplish the user's intended goals (specifically by improving the speed of transactions) may be the key to enhancing performance expectancy and, thus, adoption. This study, based on the UTAUT2 theory and previous arguments and findings, aims to predict individuals' perceptions of the usefulness of crypto-assets as a key motivating attitude towards new technology. The study posits that innovative attributes alone may not be sufficient to explain adoption. In other words, the present study postulates that positive attitudes of individuals towards blockchain-based crypto-assets in terms of performance expectancy can facilitate their adoption.

1.3.2. Effort expectancy and crypto adoption

Unlike performance expectancy, effort expectancy denotes the perceived ease of utilizing a technology (Bommer et al., 2023; Davis, 1989; Misra et al., 2022; Venkatesh et al., 2003, 2012). In other words, it refers to how individuals perceive the ease of use of new technology. Past new technology adoption-based research has likewise shown there is a positive effect of effort expectancy on individuals' behavioral intention to adopt technology in the future (Venkatesh et al., 2003). Several prior studies have demonstrated that effort expectancy plays a critical role in shaping an individual's behavioral intention to use crypto, substantiating its role as a significant and independent factor in

Source: Authors' development using Smart PLS 4.

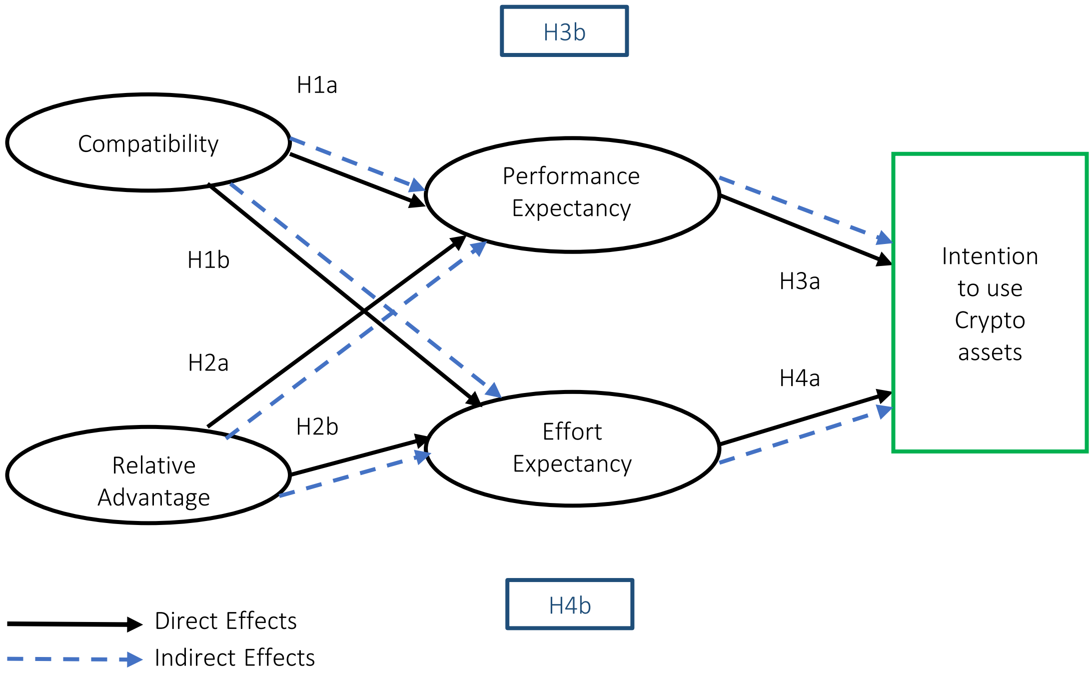

Figure 1. Conceptual model

crypto adoption alongside performance expectancy. These studies include those by Arias-Oliva et al. (2019), Bharadwaj and Deka (2021), Jariyapan et al. (2022), Kumpajaya and Dhewanto (2015), Nseke (2018), Shahzad et al. (2018), Ter Ji-Xi et al. (2021), and Kala and Chaubey (2023). On the other hand, Yeong et al. (2022) found that the perceived ease of use of blockchain-based crypto did not drive individuals' intention to use or adopt it. Therefore, they did not consider it a decisive factor in determining whether individuals would actually use or adopt it. Based on the UTAUT2 theory (Venkatesh et al., 2012) and previous arguments and findings, this study aims to predict individuals' perceptions of the ease of using crypto-assets as a secondary motivational attitude towards new technology. The authors believe that innovative attributes alone may not be sufficient to explain adoption. In other words, the current study suggests that a positive attitude towards blockchain-based crypto-assets, particularly in terms of perceived effort expectancy, can facilitate their adoption.

In summary, the existing literature highlights a variety of technological and behavioral drivers of crypto-asset adoption, yet there is a lack of consensus regarding their interplay in highly developed digital infrastructures. This study addresses this gap by synthesizing IDT and UTAUT2 to examine how technological characteristics – specifically compatibility and relative advantage – link to individual motivational factors (performance and effort expectancy) and subsequent adoption intentions.

The purpose of this study is to examine the role of technological characteristics and human motivations in shaping crypto-asset adoption intention, with particular emphasis on a developed economy – Czechia. Thus, based on the arguments and discussion above, the following hypotheses have been framed:

H1a: Compatibility has a positive effect on performance expectancy.

H1b: Compatibility has a positive impact on effort expectancy.

H2a: Relative advantage has a positive effect on performance expectancy.

H2b: Relative advantage has a positive impact on effort expectancy.

H3a: Performance expectancy positively affects intention to use crypto-assets.

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H3b: Performance expectancy mediates the relationship between compatibility and intention to use crypto-assets.

H4a: Effort expectancy positively affects intention to use crypto-assets.

H4b: Effort expectancy mediates the relationship between relative advantage and intention to use crypto-assets.

Thus, based on the literature review and subsequently framed hypotheses, the authors proposed the following conceptual model (see Figure 1).

2. METHODOLOGY

2.1. Research design

This study examines intention to adopt crypto-assets through a multi-analytical framework based on IDT and UTAUT2. The theoretical model is based on two critical characteristics of technology (compatibility and relative advantage), and human motivations (performance and effort expectancy). To assess participants' behavioral intention and subjective perceptions, structured self-report questionnaires were employed (Kasza et al., 2024).

The analytical procedure was executed in a dual-stage approach to ensure statistical robustness and predictive depth to accomplish the purpose of this study. In the first stage, the use of partial least squares structural equation modelling (PLS-SEM), using SmartPLS 4 (v. 4.1.0.0), helped to confirm the linear associations and the validity of the theoretical framework. While PLS-SEM excels in hypothesis testing and identifying linear relationships, it may overlook non-linear compensatory effects. In the second stage, an Artificial Neural Network (ANN) was deployed using IBM SPSS as a complementary predictive tool to capture non-linear relationships, enhancing the model's overall explanatory power (Tan et al., 2014; Liébana-Cabanillas et al., 2018). The variables were operationalized based on established scales: Relative Advantage (RA), Compatibility (CB), Effort Expectancy (EE), and Performance Expectancy (PE), with Intention to use crypto (IU) as the primary endogenous construct. Consistent with technology acceptance literature (Davis, 1989; Venkatesh et al., 2003), intention to adopt and use are treated as conceptually equivalent constructs here, as both reflect behavioral intention prior to actual adoption; post-adoption behaviors (e.g., continuance) remain outside this study's scope.

2.2. Sampling procedure

The target population for this study is adults from Czechia who use digital financial services and have a basic understanding of crypto-assets. Czechia was selected as a representative high-stability financial environment (CZSO, 2025; EC, 2024, 2025; IMD, 2023), offering a unique, technologically advanced context to study crypto-asset adoption among digitally proficient users within a resilient banking sector.

The data were collected through stratified random sampling to ensure the representation of various age groups, genders, educational levels, and geographic areas, allowing for a more comprehensive analysis. This tailored sampling approach was employed to enhance the representativeness of the findings and to mitigate potential bias. Moreover, these strata were selected as previous examinations have indicated that demographic and geographical characteristics may have an influence on an individual's awareness, risk perception, and adoption behavior. Before collecting the sample, respondents were screened based on predefined criteria, such as respondents below 18 years were not included, only those who are residents of Czechia were included, and those who have a basic understanding of crypto-assets were included.

Primary data were collected by administering face-to-face questionnaires from March to October 2023. The researchers also conducted a preliminary assessment of performance using G*Power 3.1.9.4 software to determine the minimum required sample size for the analysis. In this case, the researchers aimed for a mean impact of 0.15 with a 95 per cent confidence level. The sample size of 387 participants was determined to be sufficient based on the analysis conducted with the G*Power software, as it met the minimum requirement recommended by Bagozzi and Yi (2012) (see Table 1).

2.3. Questionnaire design

The present study designed a survey instrument to assess the validity of the suggested theoretical framework, using components derived from well-established theories. The questionnaire comprises two distinct sections, one of which pertains to demographics. The second section of the questionnaire has all items that require responses on a five-point Likert scale. To avoid the influence of common method bias (CMB), the study employed reverse scaling and blending techniques (Podsakoff & Organ, 1986). Also, to eliminate the potential presence of CMB, the study conducted Harman's single-factor test, which yielded results below the established threshold.

Table 1. Sample profile

Description		Frequency	Percentage
Gender	Male	215	56
	Female	172	44
Age	Between 18-28	122	32
	29-38	156	40
	39-48	83	21
	Above 49	26	7
Income (CZK)	0-10k	69	18
	11k-20k	97	25
	21k-30k	100	26
	31k-40k	39	10
	Above 40k	82	21
Education	Elementary	0	0
	Secondary	141	36
	Bachelors	206	54
	Masters	40	10

3. RESULTS

The Smart PLS 4 software was used for PLS-SEM analysis, as this analytical approach is frequently observed in the field of behavioral research, whereby cross-sectional data are employed to investigate intricate associations. Furthermore, the proposed technique can handle non-normality of data, as demonstrated by previous studies (Ringle et al., 2015; Sarstedt et al., 2020). At this juncture, the factor loadings of the indicators were computed, and those indicators that did not exhibit the anticipated loadings of 0.70 were eliminated from subsequent analysis. This study employed Cronbach's Alpha, Composite Reliability, Average Variance Extracted (AVE), and Heterotrait-Monotrait Ratio of Correlations (HTMT) scores to assess the reliability, convergent Validity, and discriminant Validity (Henseler et al., 2009, 2014, 2015; Hair et al., 2014). These measures were derived as part of the analysis.

Construct reliability was assessed using Cronbach's alpha and composite reliability, which were required to exceed a threshold of 0.7.

The reported average variance extracted (AVE) values in the study were all more than 0.5, providing additional support for the convergent validity of the measures (refer to Table 2) (Hair et al., 2017, 2019).

Table 2. Reliability and validity of constructs

Construct	Item	Factor Loading	Cronbach's Alpha (α)	Composite Reliability (rho_a)	AVE
Compatibility (CB)	CB2	0.731	0.785	0.788	0.609
	CB3	0.766			
	CB4	0.851			
	CB6	0.769			
Effort Expectancy (EE)	EE2	0.729	0.725	0.732	0.548
	EE3	0.700			
	EE4	0.826			
	EE5	0.703			
Relative Advantage (RA)	RA1	0.886	0.842	0.845	0.760
	RA2	0.887			
	RA3	0.841			
Performance Expectancy (PE)	PE1	0.824	0.788	0.788	0.702
	PE2	0.833			
	PE3	0.858			
Intention to use crypto (IU)	IU2	0.782	0.861	0.877	0.708
	IU5	0.896			
	IU6	0.888			
	IU7	0.793			

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The HTMT values were below the threshold (Henseler et al., 2015), suggesting that the constructs exhibit an acceptable amount of dissimilarity, as noted by Hamid et al. (2017) (Table 3).

The VIF values were computed and varied from 1.356 to 1.155, indicating that they fall within the collinearity threshold (Hair et al., 2014; Becker et al., 2015).

3.1. Assessment of the structural model

Two-tailed percentile bootstrapping was used to examine the hypotheses, using 10,000 replicates and a 5-per cent threshold for significance.

Analysis revealed that compatibility has a positive impact on Performance and Effort expectancy with ($\beta = 0.665$, $p < 0.001$) and ($\beta = 0.294$, $p < 0.001$), respectively, leading to the acceptance of the formulated hypotheses *H1a* and *H1b*. The other key variable of the model, Relative advantage, has a positive effect on the Effort expectancy with ($\beta = 0.255$, $p < 0.001$) supporting the formulated hypothesis *H2b* but failed to register a significant impact on Performance expectancy at a 5-per cent threshold with ($\beta = 0.014$, $p > 0.05$), causing the rejection of hypothesis *H2a*. The drivers of technology adoption performance and effort expectancy registered a significant impact on intention to use crypto-assets ($\beta = 0.218$, $p < 0.001$) and ($\beta = 0.334$, $p < 0.001$), leading to acceptance of formulated hypotheses *H3a* and *H4a*.

The examination of effort and performance expectancy as a mediating variable between Compatibility (COM) and Intention to Use (IU), and between RA and IU revealed mixed results, with CB-PE/EE-IU depicting strong statistical impact, while RA-PE/EE-IU depicts a relatively weaker relationship (see Table 4 and Figure 2). Overall, the findings suggest that human motivation factors such as EE and PE act as a key mediating variable affecting intention to use with drivers of technology such as CB and RA.

To complement the explanatory findings of the PLS-SEM methodology, the examination further employed an Artificial Neural Network (ANN) as a complementary predictive technique. While PLS-SEM was applied to test the hypothesized linear relationships and mediation effect, ANN was applied to address potential non-linearity and as-

Table 3. Discriminant validity

Variable	CB	EE	IU	PE	RA
CB					
EE	0.545				
IU	0.552	0.515			
PE	0.854	0.468	0.41		
RA	0.634	0.511	0.62	0.435	

Table 4. Hypothesized relationships

Hypotheses	Relationship	Original sample (path coefficient)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Direct effect					
H1a	CB → PE	0.665	0.04	16.71	p < 0.001
H1b	CB → EE	0.294	0.055	5.35	p < 0.001
H2a	RA → PE	0.014	0.049	0.29	0.768
H2b	RA → EE	0.255	0.052	4.95	p < 0.001
H3a	PE → IU	0.218	0.055	3.99	p < 0.001
H4a	EE → IU	0.334	0.051	6.48	p < 0.001
Indirect effect					
H3b	CB → PE → IU	0.243	0.036	6.73	p < 0.001
H3b	CB → EE → IU	0.098	0.024	4.14	p < 0.001
H4b	RA → PE → IU	0.003	0.011	0.28	0.776
H4b	RA → EE → IU	0.085	0.029	3.057	p < 0.002

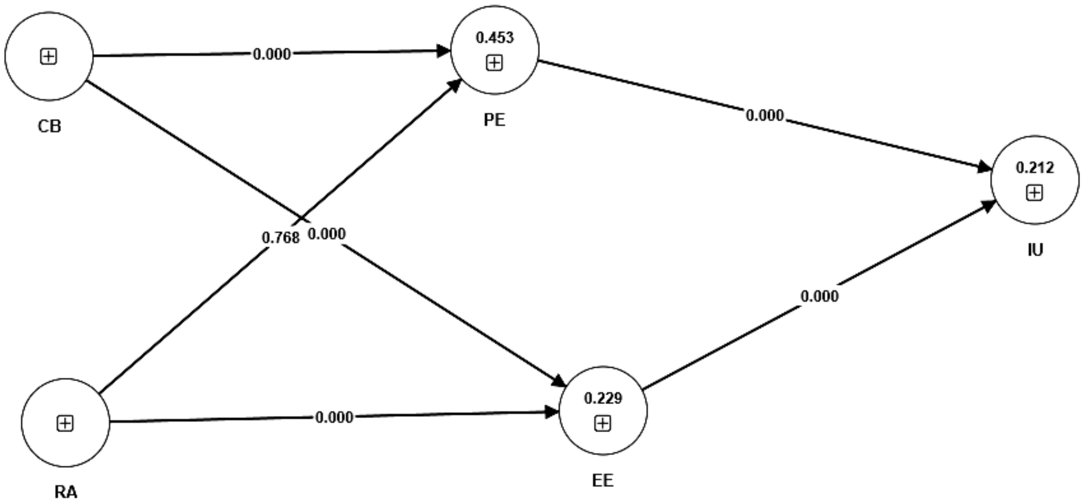

Figure 2. Author-generated model using Smart PLS 4

sess the relative predictive importance of the key constructs examined in the study. Thus, ANN analysis is treated as a method to complement the findings of the PLS-SEM model rather than confirming the causal effects.

3.2. ANN analysis

The use of a multilayer perceptron ANN analysis in the study is significant because it allows for the modelling of complex relationships and patterns within the data. By employing an ANN, the study could capture the underlying patterns with reasonable predictive accuracy (Hew et al., 2019; Ooi et al., 2018). The decision to use one hidden layer in the neural network model was based on the understanding that a single hidden layer is sufficient to represent any continuous function (Negnevitsky, 2011). This choice aligns with the practices followed by numerous behavioral researchers and ensures the model's capacity to capture the complexity of the data while maintaining computational efficiency (Liébana-Cabanillas et al., 2018; Ooi et al., 2018).

Using a ten-fold cross-validation approach, 70% of the data was used for training and 30% for assessing the networks to prevent overfitting concerns (Talukder et al., 2020; Akhtar et al., 2025). In this study, the root mean square error (RMSE) was measured for both the testing and training phases of each iteration of the ANN model. The average RMSE values during testing (0.560) and training (0.547) (Table 5) indicate acceptable predictive accuracy of the model.

Table 5. RMSE values during testing and training stages (N = 387)

Network	Training set SSE (IU)	Testing set SSE (IU)	Training set RMSE (IU)	Testing set RMSE (IU)
ANN1	89.381	38.048	0.562	0.605
ANN2	64.578	33.072	0.493	0.523
ANN3	91.865	37.652	0.582	0.570
ANN4	83.021	34.509	0.545	0.568
ANN5	90.205	37.961	0.586	0.553
ANN6	76.029	31.487	0.535	0.510
ANN7	80.899	36.723	0.543	0.570
ANN8	74.763	42.909	0.544	0.566
ANN9	81.544	34.834	0.547	0.553
ANN10	75.125	41.888	0.532	0.586
Mean	80.741	36.908	0.547	0.560
Std Dev	8.028	3.435	0.025	0.026

Finally, a sensitivity analysis was conducted to assess the relative importance of each input neuron. Following the approach of (Beres & Hawkins, 2001), this analysis ranks the exogenous characteristics based on their normalized importance, effectively highlighting the contribution of each independent variable to the model's predictive power. The Artificial Neural Network (ANN) sensitivity analysis findings are presented in Table 6. The analysis revealed that Compatibility (CB) was the most influential variable in this study (91.5% average relative importance), followed by Relative Advantage

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(RA) (79.9%), Effort Expectancy (EE) (50.9%), and Performance Expectancy (PE) (20.5%). These results suggest that technology-specific characteristics show higher predictive relevance for adoption intention than human motivational factors within this research context.

Table 6. Sensitivity analysis with normalized importance

Neural Network	CB	EE	PE	RA
ANN1	66.4%	50.2%	15.6%	100.0%
ANN2	100.0%	40.6%	24.7%	39.4%
ANN3	49.1%	21.0%	12.3%	100.0%
ANN4	100.0%	51.5%	28.7%	61.1%
ANN5	100.0%	47.1%	5.6%	78.2%
ANN6	100.0%	59.6%	24.0%	89.5%
ANN7	100.0%	59.8%	15.7%	63.4%
ANN8	100.0%	50.0%	15.1%	94.1%
ANN9	100.0%	77.7%	36.6%	97.5%
ANN10	100.0%	51.7%	27.0%	75.8%
Average relative importance	91.5%	50.9%	20.5%	79.9%

4. DISCUSSION

The current study applies an integrated IDT and UTAUT2 theoretical model to examine the intention to adopt crypto-assets among the population in Czechia. Crypto-assets are gaining popularity in developing and developed nations; however, when it comes to technologically developed countries like Czechia, the pace of crypto adoption is rather sluggish. Therefore, the current examination offers valuable insights to researchers and policymakers about the factors affecting the intention to adopt crypto-assets in a developed nation. The study examined how compatibility and relative advantage, key attributes of innovation, impact individual motivation for technology adoption, performance expectancy, and effort expectancy, ultimately affecting the propensity to utilize crypto-assets.

The findings revealed that compatibility significantly impacts performance and effort expectancy. This aligns with previous research, which identified compatibility as the most important variable affecting crypto-asset adoption (Liang et al., 2021). Further, the current examination also makes a major contribution by linking the viability component of technology adoption (Compatibility) with variables signifying human motivations (performance and effort expectancy). Therefore, compatibility's pivotal role in shaping performance and effort expectancy signifies its importance in crypto adoption. It implies that the readiness of the current infrastructure and support system that enables the adoption of technology is the key innovative attribute that impacts the two major drivers of technology performance and effort expectancy. However, this is different from the findings of the previous research (Frederiks et al., 2022), where compatibility was identified as having a marginal impact only. This signifies compatibility's role as innovation characteristics change from country to country. The examination, which identified it as having a marginal effect, was conducted in the Netherlands, which ranks second in the World Digital Competitiveness rankings.

In contrast, the ranking of Czechia, where this examination is conducted, is 24th (IMD, 2023). Therefore, nations with better technological infrastructure are better equipped to deal with technological advancements, and compatibility is relatively easy for such nations. This outcome is further established by the sensitivity analysis findings, which reveal that compatibility has an average relative importance of 91.5 per cent amongst the chosen predictors of crypto-assets.

The other key innovation variable is relative advantage, which signifies superiority over the existing alternative (Rogers, 1995). This reflected a significant impact on effort expectancy but failed to affect performance expectancy. This is in line with the available research wherein the functional superiority of the new technology is argued as a key predictor of adoption (Liang et al., 2021; Arts et al., 2011). However, since relative advantage affects only effort expectancy but fails to register a significant impact on performance expectancy, this also aligns with previous research that argues relative advantage holds slightly less weight than compatibility when adopting an innovation (Arts et al., 2011). In contrast, in a developed nation's case, compatibility and effort expectancy signify the superiority of crypto-assets, as most of the population is already well-linked with conventional finance options – a context in which crypto-assets are more likely to coexist with rather than replace fiat currencies (Yu, 2022). The ANN analysis findings also revealed that relative advantage stands next to compatibility, with 79.9 per cent in terms of average normalized importance.

The two variates of human motivation to adopt a technology, namely performance and effort expectancy, reflected a positive impact on intention to use crypto-assets, which is in line with the previous literature (Jariyapan et al., 2022; Bharadwaj & Deka, 2021). Moreover, the analysis further revealed that performance and effort expectancy mediate the relationship between compatibility and intention to use crypto-assets, and relative advantage and intention to use crypto-assets, respectively. This means that compatibility significantly affects the intention to use crypto-assets through performance expectancy. The belief that existing infrastructure is sufficient to support the adoption of the digital assets (compatibility) interacts with the individual motivation that the new technology meets their expectation criteria (performance expectancy) and offers desired advantages over existing alternatives, significantly impacting intention to use crypto-assets. Similarly, the relative advantage that crypto-assets hold over conventional currencies interacts with effort expectancy (the level of effort required to use new technology), thereby leading to a significant impact on intention to use crypto-assets. This signifies that, along with the innovative characteristics of the technology, performance enhancement and effortlessness are the key human motivations driving the adoption of crypto-assets.

Thus, the study establishes that while technological characteristics form the dominant framework for adoption, individual motivations remain a vital complementary force. The ANN sensitivity analysis confirmed this hierarchy, with EE (50.9%) and PE (20.5%) playing a meaningful but secondary role relative to Compatibility (91.5%) and Relative Advantage (79.9%). Among the two motivational factors, effort expectancy exerted a stronger direct influence on immediate adoption intention ($\beta = 0.334$) compared to performance expectancy ($\beta = 0.218$), suggesting that in a high-financial-inclusion environment, reducing perceived complexity is a more critical driver than emphasizing performance gains.

Given that technological attributes (Compatibility and Relative Advantage) currently overshadow human motivations in the developed economy, future research should explore the 'institutionalization of compatibility' under the upcoming MiCA regulatory framework. To enhance the generalizability of our findings, comparative and longitudinal studies are needed to contrast the Czech context with other developed economies characterized by high financial penetration and highly stable financial systems. Such cross-border analyses could reveal whether the identified dominance of effort expectancy over performance utility persists across different levels of digital maturity. Finally, applying this framework to Central Bank Digital Currencies (CBDCs) could test whether sovereign backing reconfigures the hierarchy of adoption determinants in high-stability markets.

CONCLUSIONS

The purpose of this study was to evaluate how technological attributes and human motivations interact to shape crypto-asset adoption intention in Czechia. By employing a dual-stage analytical framework, the research sought to move beyond linear observations and uncover the hierarchical importance of factors influencing potential users in a developed digital landscape.

The current examination offers useful theoretical and practical implications for researchers and policymakers. The findings suggest that innovation characteristics – specifically compatibility and relative advantage – show the highest predictive relevance for adoption intention, priming individual psychological motivations. The analysis reveals that in the Czech context, the readiness of infrastructure and the perceived fit with daily life (compatibility) are the primary engines of adoption, significantly influencing both performance and effort expectancy. While individual motivations remain vital, their role is largely determined by these underlying technological perceptions. This suggests that the interplay between technology and the individual varies by geographic and economic context; in highly developed nations, the seamless integration of technology into existing systems is a more critical precursor than in developing regions.

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For policymakers and financial regulators, these results suggest that adoption strategies in developed economies should prioritize reducing structural and operational complexity over promoting financial benefits. Given that compatibility emerged as the dominant predictor (normalized importance 91.5%), crypto-asset platforms that align with users' existing technological infrastructure, values, and daily practices – rather than requiring adaptation to new paradigms – are more likely to achieve mainstream uptake. For practitioners, the strong direct effect of effort expectancy on adoption intention ($\beta = 0.334$) implies that perceived ease of use and operational simplicity are more actionable levers than performance-based marketing alone in high-financial-inclusion markets.

This study is not without limitations. The cross-sectional design precludes causal inference, the single-country sample limits generalizability, and reliance on self-reported data introduces potential response bias. Furthermore, ANN normalized importance reflects predictive relevance rather than causal relationships, and findings derived from this method should therefore be interpreted with caution. Future research should address these constraints through longitudinal, multi-country designs and should examine whether the identified hierarchy of adoption determinants persists under emerging regulatory frameworks, or shifts when applied to sovereign-backed instruments such as Central Bank Digital Currencies.

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