Behavioural clusters of cryptocurrency users: Frequencies of non-speculative application domains

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Abstract: Cryptocurrency markets are still mostly associated with speculation and investment. Accordingly, most surveys to date focus solely on the prevalence of these use cases and the associated user motives while neglecting the wide range of other application areas. These include accessing services, making payments, preserving privacy, or voting on projects' governance decisions. Based on a representative, cross-sectional survey among 3,864 German citizens, this study discloses the black box of usage patterns by cryptocurrency users (N = 357). Using a generalised distance measure (GDM2) and partitioning around medoids (PAM) method on the frequency of use across eight application domains, three distinct clusters are identified. The clusters differ noticeably in terms of the frequency of accessing services ($H(2)=260$, $p=.00$), payments ($H(2)=257$, $p=.00$) and voting ($H(2)=254$, $p=.00$), which indicates that for certain user groups, speculating and investing are not the major use cases for cryptocurrency. The frequencies across all domains are similar within each of the three clusters, outlining passive investors, all-out activists and moderate conservatives. The findings contribute to research on cryptocurrency adoption, have implications for cryptocurrency regulation and provide the cryptocurrency industry with an improved understanding of their users.

Keywords: Cryptocurrency, Technology adoption, Blockchain technology, Cluster analysis, Usage patterns

Topics: Cryptocurrencies, Cryptocurrency adoption and transition dynamics

1. Introduction

Despite the steadily increasing societal relevance of cryptocurrency (Steinmetz et al., 2021), the concurrent growth of the academic literature on the topic (Ante, 2020a) and the far-reaching potential of the underlying blockchain technology (e.g. Chen et al., 2018; Mettler, 2016; Andoni, 2019), the nature of cryptocurrencies is still an enigma to many. Although Bitcoin was intended to serve as an alternative payment system (Nakamoto, 2008), it is today mostly thought of and used as an alternative asset for investment (Blandin et al., 2020). On the other hand, an increasing number of merchants are accepting Bitcoin and other cryptocurrencies as means of payment (Saiedi et al., 2021), and numerous companies and initiatives are working on solutions to technical shortcomings of such systems to develop them into truly viable means of payment (e.g. Poon & Dryja, 2016).

This ambiguity is not limited to Bitcoin but applies to the entire cryptocurrency world. It is due to the versatility of the industry, which is characterized by rapid innovation, producing ever new ways in which cryptocurrency can be applied. This broad potential is reflected in the apt definition by Rauchs et al. (2018), who describe cryptocurrency as system-native digital assets with varying purposes in economic coordination mechanisms of blockchain systems. Cryptocurrency regulation – what little there is of it so far (White et al., 2020) – partially recognizes this sweeping but unspecified potential by differentiating the purposes that cryptocurrencies are created for. For example, the Swiss Financial Market Supervisory Authority (FINMA) differentiates cryptocurrencies according to their functionalities and intended purposes for payment, utility, or as a security-like asset (Finma, 2018), where the ‘utility’ purpose in particular reflects the various use case beyond speculation and investment.

Despite these regulatory differentiations, the tenor of the academic literature considers cryptocurrencies as speculative or investment assets. This applies not least to most of the existing surveys on awareness, prevalence and use of cryptocurrencies (Steinmetz et al., 2021). A few studies investigated cryptocurrency use and users’ intentions to use cryptocurrencies (Mai et al., 2020; Arias-Oliva et al., 2019; Alzahrani and Daim, 2019a, 2019b; Schaupp and Festa, 2018), its use for payments (Mendoza-Tello et al., 2018), the use of Bitcoin in particular (Shahzad et al., 2018; Walton and Johnston, 2018; Baur et al., 2015) and the use of blockchain-based applications in general (Knauer and Mann, 2019). All these studies contribute to the understanding of why and how cryptocurrencies are used but none considers uses beyond financial applications, neither one indicates the importance of the considered use case. Ante (2020a) provides further evidence of the biased recognition of cryptocurrency application domains in the literature. Based on a systematic structuring of the research discourse on blockchain and cryptocurrency in the business and economics literature, the author reveals that the two major research streams refer to market economics and asset valuation, respectively. In other words, both research streams are related to the financial and investment character of the phenomenon. Only among the smaller research streams does the author identify other topics, such as other potential applications of cryptocurrency and blockchain technology, as well as research on specific features such as anonymity and transaction properties in cryptocurrency networks. Thus, applications beyond speculation and investment do feature on the research agenda, but much less prominently.

In accordance with the findings by Ante (2020a), a set of differentiable application domains for cryptocurrency can be derived from the existing literature on the topic. Such applications include the utilization of cryptocurrency in criminal activities, such as ransomware attacks, Ponzi schemes, terrorist financing, or investment fraud (Kethineni & Cao, 2020; Irwin & Milad, 2016; Pflaum & Hateley, 2013). The application for criminal activity exploits specific features of cryptocurrencies which differ from those that are sought after for investment proposes. Closely related to criminal activities, the literature reflects on the (pseudo-)anonymous features of cryptocurrencies, which enable users to disguise certain activities, e.g. for tax evasion or money laundering (Alsalami & Zhang, 2019; Dyntu & Dykyi, 2018; Bray, 2016). While there is a misconception that cryptocurrency transactions are per se anonymous (Jaquez, 2016), some cryptocurrencies indeed obfuscate identifiable transaction information, claiming complete privacy through cryptographic means (e.g. Noether, 2015), and so-called ‘mixing services’ serve to hide the input and output data of cryptocurrency transactions (Chohan, 2017; Möser et al., 2013; de Balthasar & Hernandez-Castro, 2017). Anchain (2020) estimates the financial volume that passed though cryptocurrency mixers in the first half of 2020 at $8 billion. Using cryptocurrency to disguise certain activities can thus be considered another application domain. In the remainder of this study, these two application domains are referred to as *criminal activity* and *disguise of activity*.

Beyond the utilization of specific features of different cryptocurrencies, the number of potential cryptocurrency applications greatly extends with the evolvement of systems which facilitate the implementation and operation of smart contracts (Ante, 2020b). Through the implementation of (distributed) virtual machines on the blockchain, such systems enable developers to create various types of applications, which are constructed of smart contracts (Hildebrandt et al., 2018) and are referred to as decentralized applications (DApps; Cai et al., 2018). For example, gambling DApps transparently place the operational code of the game on a blockchain, allowing gamblers to monitor inbound and outbound transactions and to verify the underlying gambling logic. While the games are accessed through common web frontends, gamblers interact with them using cryptocurrency wallets and cryptocurrency as stakes (Scholten et al, 2020).

In the light of cryptocurrency networks with extended computational capabilities, a tremendous number of projects have created DApps, in which tokens (non-native cryptocurrencies) have essential roles and are often a prerequisite for accessing and using such systems. For example, one of the most prominent applications is decentralized storage networks, which aim to connect parties searching for hardware storage space to those willing to rent out spare storage capacity on their machines (e.g. Vorick & Champine, 2018; Protocol Labs, 2017). Through complex routing and encryption mechanisms, only the seeker can retrieve the data that has previously been tranched and stored on other network participants' hardware. The most important role of the cryptocurrency in this system is that seekers must acquire the currency to make use of the network and providers are remunerated in the currency. The advantage of using this network for storage is the reduced dependence on central providers and reduced risks related to availability, cost, performance and system resilience (Benisi et al., 2020). Accessing such systems and services thus constitutes another application domain for cryptocurrency beyond speculation and investment. In the remainder of this study, this application domain is referred to as *access to services*.

While such systems could also use the native cryptocurrency of the network (e.g. Ether in Ethereum), the projects' cryptocurrency was oftentimes initially issued to acquire funding for system development (Ante et al., 2018). Many of the prominent cryptocurrency projects were partially funded through such crowdfunding formats, i.e. initial coin offerings (ICO; Moxoto et al., 2021; Adhami et al., 2018). Besides technological motives, investors participating in these funding formats intend to speculate on rising demand for the currency once the system is operating (Fisch et al., 2019). This activity has many intersections with speculating on and investing in 'established' cryptocurrencies but also differs in several respects, for example concerning the investors' risk dispositions, regulation, and the non-standardized processes of acquisition (Lahajnar & Rozanec, 2018). This application domain is referred to as *funding* in the remainder of this study.

Another example of a non-speculative application of cryptocurrency is voting (e.g. Hjálmarsson et al., 2018; Ayed, 2017) – utility tokens or cryptocurrency representing the right to vote on specific governance decisions in a project (e.g. Mosley et al., 2020). While these tokens can also be the subject of financial speculation, their use for voting purposes differs from speculation or investment in terms of the users' primary intentions to influence developments in their interests. We refer to this use case as *voting* in the remainder of this study.

Naturally, the outlined cryptocurrency applications need not exclude each other, and in particular, they do not exclude an expectation of future financial gains. Therefore we cannot rule out the possibility that even in an ostensibly non-speculative use case, financial gain is ultimately the main goal of the cryptocurrency users' engagement.

That being said, several questions arise regarding the relevance of the outlined application domains, which have not yet been adequately addressed in the literature. Although the transparent nature of the blockchain would allow an examination of transaction data, the frequencies of using the individual applications are rarely tracked due to the vast amount of data. Another problem of blockchain-level data analysis is that individuals can have multiple wallets for different uses – a multitude of wallets oftentimes cannot be associated with individuals. To address this research gap, we therefore conducted a representative survey of 3,864 Germans to address the following set of research questions: **(R1)** How frequently are the different application domains of cryptocurrency used? **(R2)** Which groups of cryptocurrency users can be identified based on the frequencies of use across the application domains? **(R3)** What are the demographic and socio-economic characteristics of these user groups and to what extent are their members mentally and financially involved in cryptocurrency?

The remainder of this paper is structured as follows. Section 2 provides information on the data, the sampling strategy and the statistical methodology. Section 3 presents the results of the descriptive and multivariate analyses. The former sheds light on the frequencies of using the applications domains, whereas the latter comprises the cluster analysis results and a further examination of the clusters' characteristics. The discussion of the results (section 4), an outline of their limitations (section 5) and some concluding remarks (section 6) complete this study.

2. Data and methods

The following subsections describe the structure of the survey (2.1), the variables used in the analyses (2.2) and the statistical approach (2.3).

2.1. Data collection and dataset

The primary goal of the survey, which was conducted online in February/ March 2019, was to gather representative data on the prevalence of the cryptocurrency phenomenon. The individual questions relate to cryptocurrency awareness, ownership, usage domains, socio-economics and demographics. The survey respondents are 3,864 adult German internet users – individuals who were online at least once a quarter during the previous year. The sample is representative of the German internet population with regard to age and gender. 34,440 panelists were contacted, of whom 12.6% (4,326) responded. 276 respondents were rejected based on their IP address, browser cookies or browser fingerprints in order to prevent multiple participation, and another 184 participants were dropped manually because they had answered suspiciously quickly. The manual removal of responses was performed by the panel provider based on past experience with online surveys. The excluded responses were replaced with other respondents while maintaining the representativeness of the sample. Lastly, two more participants were removed manually because their response behaviour was deemed inconsistent.

The panellists were invited by e-mail, and no indication was given as to the topic of the survey prior to participation to prevent any self-selection bias. Depending on the respondent's panel participations, personalized monetary rewards were offered. The questionnaire itself filtered the participants once according to their familiarity with the topic of cryptocurrency and, at a later stage, according to cryptocurrency possession. Participants who met neither criterion were forwarded to the socio-demographic questions.

2.2. Variables and focus groups

Information on the demographic and socio-economic variables was gathered for the full sample. Besides *Age* (the only non-binary variable) and *Male*, it includes

- educational status, which was proxied by the respondents' highest educational achievement: *NSE* (secondary education not completed), *GCSE equivalent*, *craft training*, *commercial training*, *A-level equivalent*, *higher education degree*, *PhD;*
- income class: *<500EUR*, *500–999EUR*, *1,000–1,499EUR*, *1,500–1,999EUR*, *2,000–2,999EUR*, *3,000–4,999EUR*, *>5,000EUR;*
- social status: *single*, *married*, *partnership*, *widowed*, *divorced/separated*.

All respondents were asked to report their perceived knowledge about cryptocurrency and, in the concluding question, their knowledge about blockchain technology, on a scale from zero to ten. The first question was used to filter out respondents with zero knowledge. All others were given further questions regarding their familiarity and engagement with cryptocurrency. The resulting variables that capture the respondents' level of knowledge are *Cryptocurrency*, *Blockchain technology*, and *# Coins known*, where the latter refers to the number of cryptocurrencies that the respondents had heard of and accordingly selected from a list of the top 15 cryptocurrencies by market capitalization (see the Appendix).

The remaining respondents were asked if they own(ed) any cryptocurrency (yielding the variables *Currently*, *Previously*, *Never*) and, if so, which cryptocurrencies they own(ed), to be selected from the same top 15 menu (*# Coins owned;* see the Appendix). Current cryptocurrency owners were asked to report their portfolio value by the time of the survey (*Portfolio value*), as well as the total amount of money they ever invested in cryptocurrency (excluding winnings from cryptocurrency speculation; *Investment amount*). The psychological characteristics comprise the respondents' *Trust level* [0;10] in cryptocurrency, which was only asked of respondents with non-zero knowledge, and the degree to which *Ideological motivation* [0;10] had induced current owners to buy cryptocurrency.

The central aim of the survey was to investigate how often and for what purposes cryptocurrencies are used. Current cryptocurrency owners were therefore asked to report the intensity [1;7] with which they use cryptocurrency for each of a set of pre-defined uses. The intensity was measured in days: daily (7), several times a week (6), once a week (5), several times a month (4), once a month (3), less than once a month (2), and never (1). In line with the Introduction, the following application domains were given: *Access to Services*, *Criminal activity*, *Disguise of activity*, *Funding*, *Investment*, *Payment*, *Speculation*, *Voting*, and *Other*. The latter was dismissed in the multivariate analyses because very few respondents selected it.

2.3. Statistical analysis

Cluster analysis was applied to explore the cryptocurrency users' behavioural patterns regarding the frequencies with which they engage in each application domain. The variables used for clustering are all of the ordinal type, so the generalized distance measure GDM2 was applied (Jajuga et al., 2003). Partitioning Around Medoids (PAM) was used for clustering because of its greater robustness compared to the k-means algorithm (Kaufman & Rousseeuw, 2005; Mächler et al., 2019). PAM is considered less sensitive to outliers and noise in the data because it relies on medoids as cluster centres, rather than means (Kassambara, 2017). Since the analysis revealed the distributions of the variables to be right-skewed, they were log-transformed prior to computing the distance matrix. The optimal number of clusters was selected based on the silhouette width criterion (Walesiak & Dudek, 2010). The analysis was conducted using R (R Core Team, 2021).

3. Results

3.1. Descriptive analyses

The descriptive results comprise the profiling of cryptocurrency users in terms of their demographics, socio-economics and psychological characteristics that reflect their involvement in cryptocurrency (section 3.1.1), the description of the variables that represent the application domains and their frequencies of use in response to research question R1 (3.1.2), and a correlation analysis of these variables (3.1.3).

3.1.1. Cryptocurrency user profile

Table 1 shows averages for all demographic and socio-economic indicators, in each case for the full sample as well as for subgroups determined by the status of cryptocurrency ownership (current / former / never). The typical current cryptocurrency user is predominantly male, comparatively young, well educated, and well off. Compared to non-users, current users are significantly younger, more likely to be male, better educated, and richer. Probably because of the age difference, current users are more often single, and less often divorced, separated or widowed than non-users. The comparison of current to former cryptocurrency users suggests a shift in the composition of cryptocurrency users. Current users are more likely to be male and tend to have higher incomes. It thus seems that mostly well-educated young males entered the cryptocurrency market in 2017/18, when volatility was high.

Table 1: Descriptive statistics on the demographic and socio-economic characteristics of different subsamples

	Full sample (1)	Non-users (2)	Former users (3)	Current users (4)	sign. (1) Δ (4)	sign. (2) Δ (4)	sign.(3) Δ (4)
Demographics							
Age	46.72	48.45	39.78	38.27	***	***	
Male sex	0.51	0.47	0.63	0.74	***	***	***
Education							
NSE	0.01	0.01	0.01	0.01			
GCSE eq.	0.21	0.22	0.20	0.11	***	***	***
Craft training	0.14	0.15	0.09	0.11	**	**	
Comm. training	0.22	0.23	0.14	0.22			***
A-level eq.	0.16	0.15	0.23	0.17			*
Higher ed. d.	0.25	0.23	0.32	0.35	***	***	
PhD	0.02	0.02	0.01	0.03			
Income (EUR)							
< 500	0.06	0.07	0.03	0.02	***	***	
500 - 999	0.11	0.13	0.08	0.05	***	***	*
1,000 - 1,499	0.17	0.18	0.15	0.13	**	***	
1,500 - 1,999	0.16	0.16	0.13	0.16			
2,000 - 2,999	0.22	0.21	0.28	0.25			
3,000 - 4,999	0.17	0.15	0.21	0.30	***	***	***
> 5,000	0.04	0.04	0.07	0.08	**	***	
Social Status							
Single	0.24	0.24	0.27	0.29	**	**	
Married	0.43	0.43	0.39	0.48	*	*	**
Partnership	0.20	0.19	0.29	0.17			***
Widowed	0.03	0.03	0.01	0.01	***	***	
Divorced/Seperated	0.10	0.11	0.04	0.05	***	***	
N	3,864	3,156	351	357			

*, **, *** indicate significance at the 10%, 5% and 1% level, respectively (Student's *t*-test)

Table 2 presents descriptive statistics on the respondents' self-proclaimed knowledge levels, their mental and their financial involvement in cryptocurrency. Current cryptocurrency users reported significantly greater knowledge about both cryptocurrency and blockchain technology than non-users and former users. Moreover, they knew most of the top 15 cryptocurrencies. The level of trust was significantly higher for current compared to former users. This indicates that ownership of cryptocurrency and users' perceptions of their own knowledge and their estimations of trustworthiness of cryptocurrency interrelate in certain ways, but further research is required to investigate this observation.

Table 2: Descriptive statistics on involvement in cryptocurrency

	Full sample (1)	Non-users (2)	Former users (3)	Current users (4)	sign. (1) Δ (4)	sign. (2) Δ (4)	sign. (3) Δ (4)
Knowledge							
Cryptocurrency	3.76	3.10	6.03	7.31	***	***	***
Blockchain technology	2.56	1.85	4.99	6.40	***	***	***
# Coins known	2.16	1.63	3.56	5.50	***	***	***
Mental involvement							
Trust	3.62	-	5.10	6.73	***	-	***
Ideological motivation	-	-	-	5.97	-	-	-
Financial involvement							
Portfolio value	410.18	-	-	4,439.56	***	-	-
Investment amount	197.13	-	-	2,133.69	***	-	-
# Coins owned	0.18	-	-	1.95	***	-	-
N	3,864	3,156	351	357			

*, **, *** indicate significance at the 10%, 5% and 1% level, respectively (Student's *t*-test)

3.1.2. Application domains

Figure 1 visualizes the frequencies of use of the pre-defined application domains for cryptocurrency. It shows that half of these applications were never used by most owners. Except for *other* application domains, which the respondents were asked to define themselves, all domains have right-skewed distributions – very few owners used their cryptocurrency much for any of the applications. The most frequent application domain was *investment*, followed closely by *payment*, *speculation* and *access to services*. Among the daily uses, *investment* was most often cited, followed by *disguise of activities* and *access to services*. If we add all non-zero frequencies per domain, *investment* is the most popular use by far, followed by *payment*, *speculation* and *access to services*. The application with the fewest users was *criminal activities* – although here we may suspect some degree of underreporting, despite the anonymity of the survey.

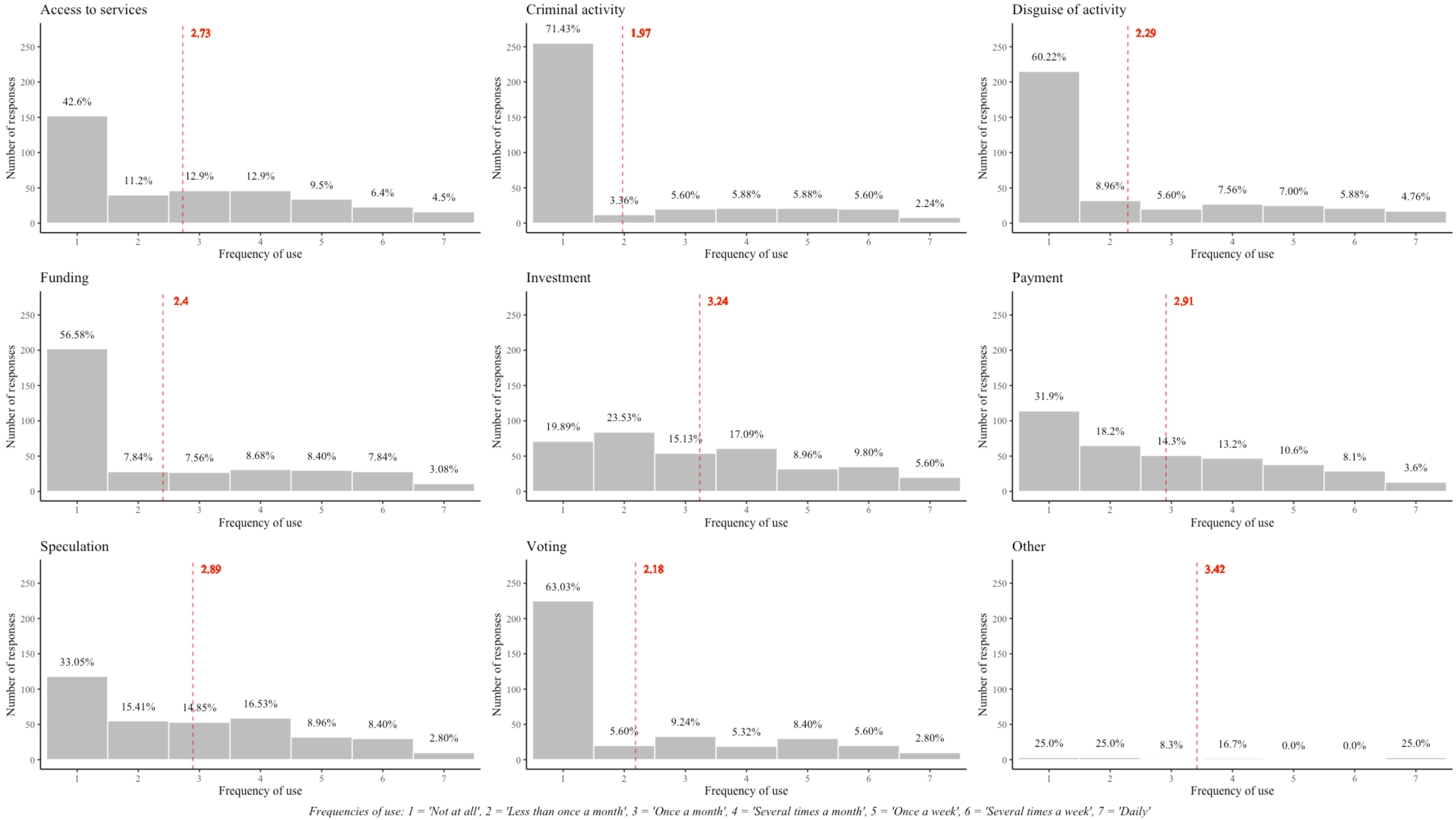

Figure 1: Distributions of the variables of the pre-defined application domains for cryptocurrency

3.1.3. Correlations

Table 3 shows the Pearson correlations among the frequency scores [1;7] of the application domains for a clearer picture of their interconnectedness. Except for *other*, the frequencies of all application domains are significantly and positively correlated with each other. This indicates that owners who engage in one application frequently (rarely) also tend to engage in other applications frequently (rarely). In other words, we are looking at a (small) group of 'heavy' users, who often rely on their cryptocurrency for several purposes, and a majority of 'light' users, who rarely make any use at all of their cryptocurrency – as already noted above. Intuitively, for example, the strong correlation between *voting* and *funding* makes sense in that users who applied their cryptocurrency for startup financing are likely to also participate in the decision-making processes of the startups. The use of cryptocurrency for such purposes of course does not preclude a users' intention to achieve a long-term (*investment*) or short-term (*speculation*) financial gain. Overall, the strong correlations among the domains reflect the complementarity of the many applications of cryptocurrencies.

Table 3: Pearson correlation matrix of the usage domains for cryptocurrency

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Access to Services	(1)								
Criminal activity	(2)	**0.64**							
Disguise of activity	(3)	**0.68**	**0.80**						
Funding	(4)	**0.72**	**0.75**	**0.76**					
Investment	(5)	**0.56**	**0.50**	**0.50**	**0.61**				
Payment	(6)	**0.77**	**0.63**	**0.64**	**0.72**	**0.54**			
Speculation	(7)	**0.60**	**0.52**	**0.55**	**0.63**	**0.53**	**0.59**		
Voting	(8)	**0.74**	**0.77**	**0.79**	**0.81**	**0.59**	**0.69**	**0.60**	
Other	(9)	-0.33	-0.41	-0.45	-0.42	-0.19	-0.36	-0.24	-0.34

Significance at the 5% level is highlighted in bold.

3.2. Multivariate analyses

The results of the cluster analysis, to which we turn next, serve to address research question R2. In subsection 3.2.2, the clusters are further explored descriptively (R3).

3.2.1. Cluster analysis results

The cluster analysis reveals three distinct clusters of cryptocurrency owners based on their frequencies of use across the eight application domains (Table 4). The clusters can be described and labelled according to two behavioural dimensions: (1) the level of engagement (frequency of use), and (2) the predominant application domains in each cluster.

Cluster 1 (n = 162) is characterized by low usage across all application domains. The most popular application here was *investment*, followed by *speculation*. This user group is labelled *passive investors*, their main interest being to achieve financial gains in the long term, more so than in the short term. Passive investors have very little interest in other applications of cryptocurrency.

Cluster 2 (n = 100) is the opposite extreme to cluster 1. Members of cluster 2 used their cryptocurrency at least on a weekly basis on average in all application domains. The most frequented application (several times a week on average) was *payment*, but other applications were similarly popular. Cluster 2 users are therefore called *all-out activists*.

Cluster 3 (n = 95) is rather inconsistent, with average frequencies of cryptocurrency use ranging from once a month for *voting* (1.60) to once a week for *payments* (3.13). As with cluster 2, but on a lower level, *payments* and *investment* were the most popular applications. In comparison to clusters 1 and 2, the frequencies of use are *tempered*. Since cluster 3 owners mostly use cryptocurrency applications that can be considered conservative, they are referred to as *moderate conservatives*.

The Kruskal-Wallis test statistics show that the most important differentiators (relative effect sizes) for the clusters are *access to services*, *payment* and *voting*. This in turn suggests that the other application domains, in particular *investment* and *speculation*, are similarly important across the clusters. Nevertheless, each cluster represents a user group with a relatively homogeneous level of frequencies across all domains. This indicates that the differentiation of user groups of cryptocurrencies is driven primarily by frequencies rather than by the applications they use.

Table 4: Average frequencies of domain usage in the three clusters

	Total			Cluster 1: *Passive investors*			Cluster 2: *All-out activists*			Cluster 3: *Moderate conservatives*			H(effect size)
	m	M	IQR	m	M	IQR	m	M	IQR	m	M	IQR	
Access to Services	2.73	2	3.00	1.21	1	0.00	4.96	5	2.00	2.97	3	2.00	260(.730)***
Criminal activity	1.97	1	2.00	1.04	1	0.00	4.00	4	3.25	1.43	1	0.00	192(.536)***
Disguise of activity	2.29	1	3.00	1.06	1	0.00	4.52	5	3.00	2.03	1	2.00	205(.572)***
Funding	2.40	1	3.00	1.09	1	0.00	4.89	5	2.00	2.03	2	2.00	249(.697)***
Investment	3.24	3	2.00	2.19	2	1.00	5.03	5	2.00	3.13	3	2.00	156(.434)***
Payment	2.91	2	3.00	1.44	1	1.00	5.09	5	2.00	3.14	3	2.00	257(.719)***
Speculation	2.89	3	3.00	1.91	1	1.00	4.81	5	2.00	2.55	3	2.00	156(.436)***
Voting	2.18	1	2.00	1.04	1	0.00	4.59	5	2.25	1.60	1	1.00	254(.712)***
N		357			162			100			95		
Silhouette avg. width		0.41			0.52			0.52			0.11		

m, M, IQR and H denote the mean, the median, the inter-quartile range, and the Kruskal-Wallis test statistic, respectively. The post hoc analysis shows that the clusters are not significantly different from each other in pairwise comparisons using Dunn's and Wilcox's test.

3.2.2. Analysis of cluster characteristics

Following the clustering of cryptocurrency owners based on their frequencies of use across the eight application domains, Table 5 presents further descriptive statistics on the average demographic and socio-economic characteristics of each cluster and their members' involvement with cryptocurrency.

Table 5: Comparison of the clusters regarding demographics, socio-economics and cryptocurrency involvement

	Cluster 1	Cluster 2	Cluster 3	H(effect size)	post hoc
Demographics					
Age	42.40	32.93	36.83	35.47(.09)***	~2:3
Male	0.73	0.77	0.72	0.84(.00)	~1:2, ~1:3, ~2:3
Education					
NSE	0.00	0.01	0.01	1.67(.00)	~1:2, ~1:3, ~2:3
GCSE eq.	0.13	0.08	0.13	1.66(.00)	~1:2, ~1:3, ~2:3
Craft training	0.10	0.07	0.15	3.06(.00)	~1:2, ~1:3, ~2:3
Comm. training	0.23	0.27	0.17	2.92(.00)	~1:2, ~1:3, ~2:3
A-level eq.	0.14	0.20	0.21	2.99(.00)	~1:2, ~1:3, ~2:3
Higher ed. d.	0.37	0.34	0.32	0.82(.00)	~1:2, ~1:3, ~2:3
PhD	0.03	0.03	0.02	0.23(.00)	~1:2, ~1:3, ~2:3
Income (EUR)					
< 500	0.03	0.00	0.03	3.18(.00)	~1:2, ~1:3, ~2:3
500 - 999	0.06	0.01	0.06	4.33(.01)	~1:2, ~1:3, ~2:3
1,000 - 1,499	0.15	0.10	0.12	1.42(.00)	~1:2, ~1:3, ~2:3
1,500 - 1,999	0.20	0.10	0.16	4.37(.01)	~1:2, ~1:3, ~2:3
2,000 - 2,999	0.21	0.32	0.23	4.18(.01)	~1:2, ~1:3, ~2:3
3,000 - 4,999	0.28	0.34	0.28	1.07(.00)	~1:2, ~1:3, ~2:3
> 5,000	0.04	0.12	0.08	5.34(.01)*	~1:2, ~1:3, ~2:3
Social Status					
Single	0.29	0.28	0.32	0.32(.00)	~1:2, ~1:3, ~2:3
Married	0.43	0.60	0.42	8.54(.02)**	~1:3
Partnership	0.19	0.10	0.22	5.61(.01)*	~1:2, ~1:3, ~2:3
Widowed	0.00	0.01	0.01	1.67(.00)	~1:2, ~1:3, ~2:3
Divorced/Separated	0.09	0.01	0.03	8.48(.02)**	~1:3, ~2:3
Knowledge					
Cryptocurrency	6.60	8.16	7.64	49.29(.13)***	~2:3
Blockchain technology	5.28	7.78	6.85	65.14(.18)***	
# Coins known	5.38	5.76	5.43	0.51(.00)	~1:2, ~1:3, ~2:3
Mental involvement					
Trust level	5.98	7.69	6.99	44.80(.12)***	
Ideology level	4.49	7.80	6.56	102.00(.28)***	
Financial involvement					
Portfolio value	4538.00	8134.00	7247.00	13.13(.03)***	~2:3
Investment amount	1687.00	2331.00	5030.00	8.12(.02)**	~1:3, ~2:3
# Coins owned	1.74	2.50	1.75	19.15(.05)***	~1:3
N	162	100	95		

H is the Kruskal-Wallis test statistic. The post hoc column lists pairwise comparisons of the clusters using Dunn's test and Wilcox's test; ~ indicates that the clusters are not significantly different.

The heavy users of cluster 2 are by far the youngest user group. However, the post hoc analysis reveals that the clusters are significantly different from each other with respect to only a few of the socio-economic characteristics. Notably, users in cluster 2 are three times as likely to be in the highest income class as users in cluster 1, and 50% more often than users from cluster 3. By contrast, considerable differences between the clusters exist regarding the indicators on cryptocurrency involvement. Users from cluster 2 report higher levels of *trust*, *ideological motivation*, and *knowledge* about cryptocurrency and blockchain technology. Also, they can be considered the most successful investors, having increased their portfolio values by 349% on average, compared to 269% in cluster 1 and 44% in cluster 3. The relative effect sizes of the Kruskal-Wallis tests indicate that the clusters are most suitably differentiated by *ideological motivation*, followed by *knowledge* about blockchain technology, about cryptocurrency, and *trust*.

4. Discussion

The ambition of this study was to improve the understanding of the phenomenon of cryptocurrency usage by investigating the users' behavioural patterns across a diverse set of application domains, which were derived from the current literature. This section discusses the extent to which the results serve to answer the stated research questions and puts them into the context of the current literature.

The present study confirms that cryptocurrencies are mostly used for financial purposes, i.e. *investment*, *payment* and *speculation*. With reference to the results by Ante (2020a), this means that there are certain parallels of the actual frequencies of use of the application domains for cryptocurrency and the importance of research streams in the literature. Yet the results allow a more granular picture of the relative importance of several application domains. While not cited as frequently as *investing* and *speculating*, other uses, such as *funding* or *accessing services*, constitute critical functionalities of cryptocurrencies to many users. The study results thus provided response to research question R1. By revealing the relevance of non-speculative application domains, the results support the findings by White et al. (2020) who conclude that cryptocurrency, i.e. Bitcoin, more closely resembles a technology-based product rather than a currency or a security.

While the relative importance of application domains is a high-level indicator of the way cryptocurrency is used in general, the identification of cryptocurrency user groups constitutes a novel insight on the user level. These user groups are distinguished not only by the frequencies of use but also by the purposes for which the cryptocurrency is mostly applied. In response to research question R2, the cluster analysis has identified three clusters. While two of them mark the extreme ends of the spectrum in terms of frequency, a third cluster comprises users with comparably inconsistent but more moderate frequencies across the domains. This homogeneity of frequencies within the clusters and the heterogeneity between the clusters makes the frequency of use an important differentiator of user groups. This finding is further confirmed by the correlation analysis, which shows that high frequencies in one application domain are associated with high frequencies in the others. Besides frequency, the relative importance of the application domains within the clusters is another important differentiator. While *investing* is the dominant purpose in cluster 1, users in cluster 2 and 3 use cryptocurrency most often for *payments*. And while *investing* is an important aim in all clusters, clusters 2 and 3 highlight the importance of other use cases. For example, owners in cluster 2 use cryptocurrency for *accessing services* and *funding* almost as often as for *investing*. This distinction of user types adds more detail to existing research on the profiles of cryptocurrency users by Steinmetz et al. (2021), Mai et al. (2020) and Arias-Oliva et al. (2019), and it provides stakeholders in the cryptocurrency ecosystem with an improved understanding of their users' behavioural patterns. For example, frequent users are especially associated with cryptocurrencies that enable them to *access services* or exercise *voting* rights.

In response to research question R3, the results provide a detailed overview of the demographic, socio-economic, psychological and financial characteristics of the identified clusters, or user groups. Importantly, the post hoc analyses of the Kruskal-Wallis tests show that the clusters do not differ significantly in terms of their socio-economic characteristics. This finding confirms previous research to the effect that while the comparatively small number of cryptocurrency user are quite distinct from the general (internet-using) population, the group itself is rather homogeneous (Steinmetz et al., 2021). In contrast to the socio-economics, the users' mental involvement in cryptocurrency differed significantly across the clusters. This applies to *knowledge* about *cryptocurrency* and *blockchain technology*, as well as to the levels of *trust* and *ideological motivation*. The analysis discloses that higher levels of mental involvement, as operationalized by these variables, does tend to coincide with greater engagement (frequency of use).

Regarding the financial involvement of the different user groups, it is particularly interesting that the frequency of engagement and the prioritization of applications do not correspond to the users' financial success, nor to the volume of their initial investment. On average, the return on investment was higher for the least active users (cluster 1) than for those with a moderate frequency (cluster 3). With respect to the prioritization of applications, the results do not indicate that financial success is associated with any specific application. Also, the financially more successful users reported lower levels of knowledge and mental involvement. This finding adds to the literature in that while higher levels of *trust*, *ideology*, and knowledge on *cryptocurrency* and *blockchain technology* raise the probability of being a cryptocurrency user (Steinmetz et al., 2021), these variables do not predict financial success or initial investment. Regarding the discourse on the investment behaviour of cryptocurrency users (e.g. Ante et al., 2020c), the present results broaden the perspective by addressing the interrelation between the frequency of use and investment performance.

5. Limitations and future research

This study is subject to limitations regarding its design, the interpretability and generalizability of the results, and the choice of application domains. With the survey being conducted online, there was no scope for providing personal instructions to and answering queries from the respondents. Further, internet users who volunteer for a panel may not be representative of all internet users. While the sample is representative of German internet users in terms of age and gender, the proportion of cryptocurrency users in this sample may be larger than the proportion among all internet users. Since the study design is cross-sectional, there is a risk of selection bias and information bias (Wang & Cheng, 2020). For example, information bias may arise in the form of observer bias or recall bias. Another limitation of the study design is that predictive power of cross-sectional study designs is limited because outcome and exposure variables are assessed simultaneously, and it is not possible to establish true causal relationships without longitudinal data (Solem, 2015; Carlson & Morrison, 2009). In consequence, the findings of this study are to be interpreted with care and ideally to be confirmed by further research.

Deriving the application domains from the existing literature is clearly a subjective procedure, and the domains outlined here certainly do not cover all conceivable use cases – not by the time of the survey, and even less so in the future. This limitation implies opportunities for future research to explore systematic and comprehensive methods for identifying relevant application domains for cryptocurrency. A related limitation consists in the fact that some of the application domains investigated in this study are not sufficiently distinct from each other. For example, a user might not have been able to differentiate if he was applying cryptocurrency in the context of criminal activity or for the purpose of disguising certain activities, because these application domains are intersecting. Such overlaps of purposes limit the interpretability of the results. Future research may find better ways to disentangle the various motivations to acquire and use cryptocurrency.

Further limitations ensue from deriving the relative importance of the application domains solely from the frequencies of use. Clearly opportunities to use cryptocurrencies for voting or to fund startups arise less often than, for example, opportunities for speculation. Also, the frequencies of use need not reflect the importance that the users attach to the different application domains. For example, a user might only participate in voting procedures once a month but consider this type of involvement to be much more important than his weekly cryptocurrency trades for speculation. As such, the frequency of use is but one of many viable indicators of the importance of an application domain – alternatives being, for example, the financial volume associated with an activity or the psychological importance of various application domains to the individual users. Nevertheless, future research may build on these findings, verify them for different geographic regions, and track the development of the use cases' relative importance over time. Especially in light of the enormous innovation capacity of the cryptocurrency ecosystem, the set of potential application domains requires periodic revision and extension. Additional application domains may for example concern decentralized finance (DeFi; Werner et al., 2021) or non-fungible tokens (NFT; Ante, 2021).

Lastly, there are opportunities for future research to investigate the observation that the levels of self-reported knowledge and trust are on average significantly higher than for non- or previous owners of cryptocurrency. It would be intruding to explore this observation in the context of cognitive bias (Haselton et al., 2015), self-serving bias (Sheppard et al., 2008) and system justification (Jost et al., 2004), and its relations to frequencies of use.

6. Conclusion

Cryptocurrencies continue to puzzle many observers, and this is at least in part due to their diverse range of applications. The rapid evolution of the cryptocurrency ecosystem produces ever new applications and opportunities beyond investment, speculation or payments. Based on a representative sample of German citizens, this study has investigated the relative importance of a pre-defined set of application domains. As reflected in the current literature on the topic, the most important uses for cryptocurrency are focused on financial applications, i.e. investment, payment and speculating. While use cases such as accessing services, voting, or funding of startups can be considered niche applications in general, they are frequently used by individual groups of cryptocurrency owners.

A cluster analysis served to identify three user groups, which are characterised by the frequency of using cryptocurrency, the application domains which they mostly engage in, and their mental and financial involvement. Based on the frequencies of use and the most important application domains in each cluster, the clusters can be described as *passive investors*, *all-out activists* and *moderate conservatives*. The group of heavy users may indeed be at risk of over-involvement

– a possibility that begs additional research. Nevertheless, the results contribute to the literature by refining existing knowledge on the structure of cryptocurrency users and revealing important differentiating factors for user groups being the frequency of use, primary application domains as well as mental and financial involvement.

The results have several ramifications in the realms of cryptocurrency research, the management of related businesses, and regulation. Among the scientific implications, although cryptocurrency users constitute a distinct group with homogeneous socio-economic characteristics, there is considerable variation in their behavioural and mental involvement. Beyond the expectation of financial gain, cryptocurrencies enjoy a wide range of uses, which have not been the focus of much academic research yet. Future studies should refine and extend the set of application domains and find complementary indicators to the frequency of use for deriving the relative importance of applications beyond investment, payment and speculation. In terms of managerial implications, this study's findings suggest ample scope to identify and refine target groups for cryptocurrency-based products and services. For regulators, the varying relative importance of different application domains entails that cryptocurrency must be treated as a unique asset class with a variety of meaningful use cases that extend far beyond investment and the disguise of criminal activity. For unfolding and harnessing the positive potentials of cryptocurrency, regulators should consider domain-specific regulatory treatment. Recent years have shown that the cryptocurrency ecosystem innovates at a fast rate, so the set of use cases and their relative importance are subject to constant change. The overall importance of the technology, e.g. the prevalence of cryptocurrency, is likely to evolve similarly fast. Keeping up with these developments will pose a perpetual challenge for regulation for the foreseeable future.

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Appendix

Table A1: Ownership rates among the 15 cryptocurrencies with the highest market capitalizations

	Awareness (%)					Ownership (%)	
	Full sample	Non-users	Former users	Current users	All Crypto-users	Full sample	Current users
Cryptocurrency	(1)	(2)	(3)	(4)	(3) & (4)	(1)	(4)
Bitcoin (BTC)	0.07	0.83	0.81	0.88	0.84	0.07	0.81
Ethereum (ETH)	0.02	0.19	0.13	0.32	0.23	0.02	0.26
Ripple (XRP)	0.01	0.10	0.05	0.19	0.12	0.01	0.15
Bitcoin Cash (BCH)	0.01	0.27	0.20	0.51	0.35	0.01	0.14
EOS (EOS)	0.00	0.08	0.05	0.15	0.10	0.00	0.04
Stellar Lumens (XLM)	0.00	0.05	0.03	0.12	0.07	0.00	0.04
Litecoin (LTC)	0.01	0.14	0.08	0.28	0.18	0.01	0.16
Tether (USDT)	0.00	0.05	0.03	0.11	0.07	0.00	0.03
Bitcoin SV (BSV)	0.00	0.09	0.06	0.20	0.13	0.00	0.04
TRON (TRX)	0.00	0.06	0.04	0.11	0.07	0.00	0.05
Cardano (ADA)	0.00	0.02	0.01	0.06	0.03	0.00	0.02
Iota (IOT)	0.01	0.05	0.02	0.11	0.07	0.01	0.07
Monero (XMR)	0.01	0.07	0.03	0.16	0.10	0.01	0.06
Binance Coin (BNB)	0.00	0.05	0.03	0.15	0.09	0.00	0.02
Dash (DASH)	0.01	0.11	0.07	0.21	0.14	0.01	0.07
N	3,864	3,156	351	357	708	3,864	357

The cryptocurrencies are ordered by their market capitalization at the time of the survey.

Declarations

Conflicts of interest: The author does not have any conflicts of interest to report.

Funding declaration: This research did not receive any public or commercial funding.