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Dividing the ICO Jungle: Extracting and Evaluating Design Archetypes

by

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Abstract. The sale of blockchain-based digital tokens as a novel funding mechanism, referred to as initial coin offerings (ICO), has grown exponentially, resulting in $12bn raised globally during the first half of 2018. Due to the novelty of the phenomenon, the concept is not yet entirely understood. Existing research provides first insights into ICO endeavors and design only. To date, comprehensive and in-depth analyses of ICO design archetypes to better understand prevailing ICO characteristics are missing. We bridge this gap by enriching an existing ICO taxonomy and applying a cluster analysis to identify predominant ICO archetypes. As a result, we identify five ICO design archetypes: the average ICO, the liberal ICO, the visionary ICO, the compliant ICO, and the native ICO. We thereby contribute to a comprehensive and in-depth understanding of the ICO phenomenon and its implications. Further, we offer practitioners tangible design suggestions for future ICOs.

Keywords: Blockchain, initial coin offering, ICO, cluster analysis, design archetypes

1 Introduction

Emerging digital technologies challenge existing business structures and invoke innovation [1, 2]. As one example, blockchain forces organizations to rethink and innovate their business models. Thus, while the technology's potential is not yet entirely assessed and understood, we observe increasing interest in its vast use cases from both practitioners and academics [3, 4]. In the past years, a use case in the financial service industry is attracting high attention: sales of blockchain-based digital tokens as a novel funding mechanism, referred to as initial coin offerings (ICOs) [5-9]. Despite regulatory uncertainty [10-12], ICO fundraising has grown exponentially throughout 2017 (343 ICOs) and 2018 (394 ICOs in six months) [13]. Indeed, for the first half of 2018, the Wall Street Journal reports $12bn raised in the global ICO market [14].

Due to the novelty of the phenomenon, the concept of ICOs is not yet entirely understood [5], and a number of questions - especially related to regulation - need to be

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answered in practice and academia. With regard to the ICO's inherent idea of providing open, global, and decentralized access to funding, regulation becomes very difficult [12]. Regulators and many governmental institutions have just started to take action in the so far mostly unregulated ICO market [7]. The regulation approaches, however, are neither homogeneous, nor follow an integrated global strategy. Thus, the actions range from banning ICOs to taking no action or focusing on specific ICOs only [15]. One major problem is the heterogeneity of ICOs, although there were first approaches of standardization [16]. Additionally, recent research indicates that the ICO success heavily depends on its design parameters [9, 12, 17, 18]. Therefore, in-depth analysis of ICO design variations is necessary to better understand the phenomenon and react appropriately from an economic, societal, or regulatory side.

In particular, Information Systems (IS) research and specifically sociotechnical research needs to address this information technology driven phenomenon and provide a systematic understanding, as there is a need to investigate implications of the technology [19]. Classifying the extremely heterogeneous ICOs into predominant, lucid archetypes, analyzing them, and thereby getting a systematic understanding of the emergent phenomenon contributes to the current body of knowledge. Further, it allows to establish a common understanding of ICO designs, related consequences, and the application for investors and ventures. Yet, scientific research in the young research domain of ICOs is still scarce [5, 12, 18]. Boreiko and Sahdev [9] provide an overview of the evolution of ICOs. Chanson, Risius and Wortmann [5] compare ICOs to traditional crowdfunding mechanisms and Fridgen, Regner, Schweizer and Urbach [7] propose a taxonomy to classify ICO characteristics. They furthermore suggest four possible ICO archetypes as a basis for future research. However, in the rapidly evolving ICO landscape, enhancing the taxonomy [7] by adding additional cases might reveal necessary amendments to the taxonomy and further archetypes that occurred after November 2017. Although these research projects represent first important steps into the emerging domain, to date, a comprehensive and in-depth analysis of ICO archetypes is missing. Therefore, the goal of our research project is to bridge the existing gap by empirically investigating and analyzing ICO archetypes and evaluating ICOs in a structured manner. Therefore, we define the following research question: *Which quantitatively derived and qualitatively interpreted ICO design archetypes do exist, and which design parameters do differentiate them?*

To answer this question, we conduct a cluster analysis upon the refined ICO taxonomy of Fridgen, Regner, Schweizer and Urbach [7], to initiate the next step in ICO research. Compared to this existing study, we find more reliable results by increasing the clustering performance. We conduct a two-stage clustering approach, which yields in more accurate results, as the final clusters do not depend on a random selection of initial cluster centroids. [20-22]. By doing so, we aim to make a twofold contribution: First, we propose empirically based archetypes obtained from a sound clustering methodology providing a comprehensive understanding of the ICO phenomenon and of related implications for individuals as well as economic or regulatory organizations. Second, we aim to allow practitioners to conclude on concrete design suggestions for potential future ICOs with regard to the consequences arising from specific design decisions.

2 Research Method

In this section, we give an overview on our overall research approach, and resume with a detailed introduction of our cluster analysis. To identify meaningful archetypes of ICOs, we perform a cluster analysis, in line with IS literature and the exploratory research setting [23-25]. A cluster analysis is a statistical technique with the aim to group entities of similar kind into respective clusters. The variation within groups is minimized, whereas the variance between groups is maximized [20, 21]. In general, cluster analyses are applicable to describe generic archetypes of entities [21, 26]. In IS research, according to an analysis of 55 IS articles, researchers chose this method regularly to classify observations of specific objects of interest [27].

The cluster analysis follows three basic steps: First, we select the clustering variables. In chapter 3, after giving a general overview on blockchain, ICO, and design archetypes, we therefore review existing research on ICO classification, including the ICO design taxonomy of Fridgen, Regner, Schweizer and Urbach [7]. Second, we determine the appropriate cluster algorithm. Finally, we apply statistical methods to confirm the reliability as well as the validity of the results. We report the application of the hereinafter described research method in chapter 4. The qualitative interpretation of the archetypes and the conclusion follow in the remaining two chapters, 5 and 6.

Variables: The selection of clustering variables represents a fundamental step in cluster analysis because it highly affects the outcome [28]. Following a deductive approach [29], the chosen variables need to be closely linked to extant theory [22]. For this purpose, choosing a taxonomy's dimensions is a commonly applied approach [23]. Therefore, we use the 23 dimensions of the taxonomy from Fridgen, Regner, Schweizer and Urbach [7] as distinctive variables. Some researchers propose to perform a factor analysis as a pre-process and use the resulting factor scores for the clustering [28, 30]. However, literature does not recommend this approach if the data is not suitable for factor analysis due to dropping factors may then result in suboptimal clusters [22]. Furthermore, using factors hampers the interpretability of cluster outcomes [31, 32].

A*lgorithm:* After the selection of the cluster variables, we select an appropriate clustering algorithm. The application of hierarchical or non-hierarchical algorithms is well-recognized. However, both algorithms have various limitations when applied in an isolated way [22]. Hierarchical methods (e.g., Ward's algorithm) are highly sensitive to outliers [21, 33]. Non-hierarchical procedures require pre-specifying a number of clusters, which is difficult in an exploratory study field [27]. Therefore, instead of choosing one method, researchers developed two-stage clustering to improve the clustering performance and to receive more accurate results - combining the advantages of both methods [20, 22, 28, 34]. As this represents the expert consensus among IS researchers [27], we adopt this two-stage clustering process.

Validation: As a basis for valid clusters, Hair, Black, Babin and Anderson [21] suggest finding significant differences between the selected variables for the developed clusters. Thus, we use cross tabulation analysis to identify which variables significantly contribute to the differentiation of ICO archetypes [26]. Subsequently, we conduct post-hoc tests to compare single clusters.

Data sample: To provide a comprehensive perspective on ICOs in this paper, we collect a data sample consisting of 84 ICOs with each 23 categorical data points along the taxonomy's dimensions. For this purpose, and due to the lack of an exhaustive ICO database, we create an ICO longlist through the lists published by token information providers that are perceived as most reliable in the blockchain community, such as ICObench [35], Coindesk [13], and SmithAndCrown [36]. Our sample includes ICOs from different industries and from all over the world in the period spanning from January 2013 to July 2018. As ICOs are rarely restricted to national borders and even intermix existing industries, it is very difficult to quote reliable information on the geographical origin and industry assignment.

3 Foundations

3.1 Blockchain, Initial Coin Offerings, and Design Archetypes

Blockchain is a decentral data structure that allows to store transactions immutably, chronologically, and transparently in distributed networks. Recently, a blockchain use case called ICO has become a popular alternative financing method for organizations [6, 7, 9, 11, 37]. This phenomenon emerges due to the rise of the second generation of blockchain and the establishment of smart contracts. Smart contracts are referred to as computer programs that allow to implement business logic tamper-proof in blockchains [38]. This enables the development and execution of programs that invoke secure transactions between two or more parties with no need of knowing and trusting each other [3, 33]. As smart contracts are also able to control digital assets, they enable the issuance and distribution of digital tokens that reside on top of blockchains [39]. This mechanism to create and transfer tokens is the fundamental part of any ICO. The funds raised during an ICO typically finance blockchain-related projects [40]. In this way, an ICO represents an alternative to crowdfunding in venture financing [8]. A substantial difference to crowdfunding, however, is the tradability of tokens on secondary markets. Tokens do not necessarily entail ownership of a firm but can fulfil various functions [9]. For instance, they might act as a digital share in a project or grant access to a blockchain enabled platform [41].

Since the surge of the ICO phenomenon in 2017, there has been increasing academic attention spent to analyzing various aspects of ICOs. Empirically, Adhami, Giudici and Martinazzi [17] analyze the success determinants of ICOs, gathering financial data and looking at theoretically obtained input variables. Amsden and Schweizer [12] as well as Fisch [18] propose a different definition of success including also the token's listing status. Based on these studies, Boreiko and Sahdev [9] propose a further definition of success, distinguishing between top ICOs, average ICOs, and failed ICOs. Li and Mann [11] focus on how an ICO increases social welfare and discuss governance mechanisms of an ICO thereby proposing guidance to regulators.

Furthermore, first research steps to explore the underlying classification of ICOs have been made by Fridgen, Regner, Schweizer and Urbach [7]. They applied a structured in-depth analysis of ICOs to develop a taxonomy incorporating 23 dimensions. In their research outlook, they are already able to identify four basic ICO archetypes. However, as their study is limited to k-means clustering, their results strongly depend on the selection of initial cluster centroids [20-22]. Additionally, as the cluster analysis deals with the special case of categorical data, a more powerful distance measure should replace Euclidean distances [42]. Finally, as their focus is the development of a taxonomy, their cluster analysis remains a descriptive only first step towards the differentiation of ICO archetypes. Since recent research indicates that ICO design parameters significantly influence ICO success [9, 12, 17, 18], it is of vital importance to understand and analyze predominant ICO archetypes. Soh and Markus [43] and Trice and Beyer [44] argue that the empirical identification and evaluation of archetypes is a suitable method to create understanding about multifold and complex new phenomena. Existing research indicates that a selected meta-characteristic can classify and evaluate ICOs, however, these classifications in current research draw on a rather conceptual basis [7]. Thus, building upon empirically validated design parameters and applying an in-depth two-stage cluster analysis, our study represents an important step towards a better understanding of ICOs.

3.2 ICO Classification

Since blockchain is a dynamic and a very young research area, design parameters of ICOs are continuously evolving. Therefore, we undertake a critical reflection on the taxonomy of Fridgen, Regner, Schweizer and Urbach [7]. We find its meta-characteristic *Design parameters and characteristics of ICOs* applicable for our study as it comprehensively covers both, the purpose of the taxonomy as well as the purpose of the archetypes we aim to investigate. However, it generally is a valid limitation of taxonomies that additional cases can possibly not be classified within the existing dimensions. This is why Nickerson, Varshney and Muntermann [45] require a useful taxonomy to be extendible when new types of objects appear. The restriction that taxonomies are collectively exhaustive implies that a taxonomy is not final but needs to be extended incrementally by including additional dimensions and characteristics in the course of time. Thus, we follow the advice of Nickerson, Varshney and Muntermann [45], and revise the taxonomy of Fridgen, Regner, Schweizer and Urbach [7]. From the conceptual perspective, we deduct the dimensions on the basis of related literature and of semi-structured interviews with ICO practitioners. From the empirical perspective, we iteratively examine our data sample of 84 ICO cases and classify them into the taxonomy. We find that some new characteristics and dimensions appeared in the ICO environment, and thereby add or adapt dimensions and characteristics when necessary to cover all ICO cases. As a result, we suggest enriching the model by adding further characteristics to two existing dimensions and by re-defining the characteristics of three dimensions. Table 1 shows the final overarching dimensions forming our theoretical framework.

Table 1. Taxonomy of ICO design parameters based on Fridgen, Regner, Schweizer and Urbach [7]

<table>
<tr><th>Dimension</th><th colspan="12">Characteristics</th></tr>
<tr><td>Token implementation level</td><td colspan="4">on-chain</td><td colspan="4">native</td><td colspan="4">sidechain</td></tr>
<tr><td>Token purpose/type*</td><td colspan="2">usage</td><td colspan="2">work</td><td colspan="2">funding</td><td colspan="2">staking</td><td colspan="2">equity security</td><td colspan="2">non-equity security</td></tr>
<tr><td>Token supply growth</td><td colspan="4">fixed</td><td colspan="4">adaptive inflation</td><td colspan="4">fixed inflation</td></tr>
<tr><td>Token supply cap</td><td colspan="6">capped</td><td colspan="6">uncapped</td></tr>
<tr><td>Token burning</td><td colspan="6">yes</td><td colspan="6">no</td></tr>
<tr><td>Token distribution deferral</td><td colspan="6">yes</td><td colspan="6">no</td></tr>
<tr><td>Token holder voting rights</td><td colspan="6">yes</td><td colspan="6">no</td></tr>
<tr><td>Issuing legal structure</td><td colspan="6">foundation</td><td colspan="6">limited</td></tr>
<tr><td>Team company token share</td><td colspan="4">minority</td><td colspan="4">majority</td><td colspan="4">half</td></tr>
<tr><td>Team lockup period*</td><td colspan="4">no</td><td colspan="4">single period</td><td colspan="4">multiple periods</td></tr>
<tr><td>Pre-sale before ICO*</td><td colspan="3">no</td><td colspan="3">private</td><td colspan="3">public</td><td colspan="3">both</td></tr>
<tr><td>Pre-sale discount</td><td colspan="6">yes</td><td colspan="6">no</td></tr>
<tr><td>Planned occurrence</td><td colspan="4">multiple rounds</td><td colspan="4">single round</td><td colspan="4">unspecified</td></tr>
<tr><td>Registration needed</td><td colspan="6">yes</td><td colspan="6">no</td></tr>
<tr><td>Eligibility restrictions</td><td colspan="3">none</td><td colspan="3">geographic</td><td colspan="3">accreditation</td><td colspan="3">multiple</td></tr>
<tr><td>Purchase amount limit</td><td colspan="3">none</td><td colspan="3">minimum</td><td colspan="3">maximum</td><td colspan="3">both</td></tr>
<tr><td>Auction mechanism*</td><td colspan="6">yes</td><td colspan="6">no</td></tr>
<tr><td>Sales price</td><td colspan="6">fixed</td><td colspan="6">floating</td></tr>
<tr><td>Price fixing currency</td><td colspan="6">crypto</td><td colspan="6">fiat</td></tr>
<tr><td>Funding currency</td><td colspan="4">crypto</td><td colspan="4">both</td><td colspan="4">none</td></tr>
<tr><td>Funding cap*</td><td colspan="3">none</td><td colspan="3">hard cap</td><td colspan="3">soft cap</td><td colspan="3">multiple</td></tr>
<tr><td>Time horizon</td><td colspan="4">block time</td><td colspan="4">fixed date</td><td colspan="4">open end</td></tr>
<tr><td>Time-based discount</td><td colspan="4">none</td><td colspan="4">single rate</td><td colspan="4">multiple rates</td></tr>
<tr><td colspan="13">*Extensions & changes to the taxonomy of Fridgen, Regner, Schweizer and Urbach</td></tr>
</table>

Token purpose: To the current four token purposes, we add the two novel types *Equity security token* and *Non-equity security token*. Applying SEC regulation, a token represents a security if they meet all elements of the Howey test [46]. These include that the token embodies (i) an investment of money, (ii) in a common enterprise, (iii) with an expectation of profits [47]. An equity security token bears a dividend to the token holder, see for example the TAAS token. A non-equity security token behaves like a security but represents a loan for a specified time, and the founders are able to buy back the token, see for example the ZRCoin [48].

Team lockup period: Following IPO and Venture Capital literature, we apply the more common term *lockup* instead of vesting for the dimension, referring to the time window during which owners are not allowed to redeem their tokens [49].

Pre-sale before ICO: We add the characteristic *multiple* to the dimension, since the analysis of ICO cases reveals that some ICOs follow both, a private and public pre-sale.

Auction mechanism: Empirically, we observe the Dutch auction mechanism as the only implemented one so far, however different manifestations are possible. We therefore change this dimension's characteristics into *no* and *yes* thereby subsuming all kinds of theoretical auction mechanisms.

Funding cap: The analysis of ICO cases reveals that a specified soft cap does not necessarily trigger a remaining time limit of the ICO. It generally represents a minimum funding goal the team aims to raise in order to create a minimum viable product. Sometimes, analogous to the all-or-nothing mechanism in crowdfunding [50], if the ICO fails to reach the soft cap, the issuer returns all funds.

4 Cluster Analysis and Identification of ICO Archetypes

In this chapter, we apply the aforementioned research method and provide the quantitative results of the cluster analysis. We collect a data sample consisting of 84 ICOs with each 23 categorical data points along the taxonomy's dimensions. Since we select the taxonomy's dimensions as cluster variables, we need to avoid overweighting underlying constructs. This is an issue if the clustering variables are significantly correlated [22]. Therefore, we conduct a multiple correspondence analysis (MCA), which is as an extension of a principal component analysis for categorical data [51]. We obtain low eigenvalues of the resulting factors. This indicates that we should keep the initial 23 dimensions as clustering variables.

According to the chosen two-stage clustering process, the clustering algorithm starts with the hierarchical analysis. We apply Ward's method, which is the most commonly applied algorithm among the hierarchical methods [27] due to the production of reliable cluster results [23, 24, 52]. For the distance measure between categorical data points, literature recommends using the Jaccard, the Simple Matching, and the Dice coefficient [31, 53]. We test different measures and find that all produce highly similar results [23]. We then inspect the dendrogram and the scree-plot to determine the appropriate number of clusters [20]. This step reveals that five clusters represent the optimal number of clusters as any additional cluster would not significantly lower the total within cluster sum of squares. Additionally, we compute the average silhouette width and the gap statistic [54]. They both confirm the five-cluster solution. Next, we conduct non-hierarchical clustering with the results from the Ward's method as input to pre-specify the number of clusters. Among IS studies, researchers widely use the k-means approach with Euclidean distance measure [27]. However, research indicates that k-means is not the optimal approach to process categorical data since Euclidean distances are not meaningful on a discrete sample space [55]. Huang [56] therefore proposes a non-hierarchical clustering algorithm called k-modes, using a simple dissimilarity measure and substituting the means of the clusters with modes [33, 55]. The application of the k-modes algorithm to the dataset results in our five final clusters. Subsequently, we apply Pearson's χ^2 and Cramer's V, measures for the strength of a relationship, to analyze global differences across all clusters in the categorical data points [23, 24]. To compare single cluster differences, we use Pearson's χ^2 with correction for alpha inflation (Bonferonni style).

Table 2 provides an overview of the cluster analysis results. The results indicate the significant contribution of the taxonomy's ICO design dimensions chosen as cluster variables to the differentiation of ICO archetypes. The Chi-square reports significant values for most cluster variables, and the Cramer's V reports medium to strong association. The exceptions reflect some sales terms variables, i.e. the funding currency and the fixing of the price, closely related to the auction mechanism, as well as two time-related sales terms. Analysis reveals that the information gained from these variables is low, and there is low variation among clusters. We also conduct the clustering without these variables and received nearly identical results. Thus, in order to not lose information, we keep the variables in the taxonomy [45], as we perceive them as important dimensions in the overall characterization of ICOs.

Table 2. Results of cluster analysis

Dimension	**Cluster**					**Significance tests**		
	1 n=29	**2 n=20**	**3 n=19**	**4 n=9**	**5 n=7**	**$\chi^{2\ a}$**	**V [b]**	**Pairwise post-hoc tests [c]**
Implementation level	onchain 93%	onchain 80%	onchain 84%	onchain 100%	native 86%	34.42 ***	0.453 **	1-5***;2-5***;3-5***
Purpose/ Type	usage 59%	usage 80%	usage 42%	usage 78%	staking 71%	27.73 *	0.287 *	
Supply growth	fixed 90%	fixed 80%	fixed 84%	fixed 89%	fix infl. 71%	47.87 ***	0.534 ***	1-5***;2-5***;3-5***;4-5**
Token supply cap	capped 97%	capped 90%	capped 89%	capped 100%	uncap. 100%	46.8 ***	0.746 ***	1-5***;2-5***;3-5***;4-5**
Token burning	no 72%	no 90%	no 58%	yes 89%	no 100%	22.64 ***	0.519 ***	1-4**;2-4**;4-5**
Distrib. deferral	yes 66%	no 70%	no 63%	yes 56%	yes 86%	10.95 *	0.361 **	
Holder voting rights	no 90%	no 90%	yes 63%	no 89%	yes 71%	27.53 ***	0.572 ***	1-3**;1-5**;2-3**2-5**
Issuing structure	limited 90%	limited 75%	limited 100%	found. 67%	found. 57%	23.69 ***	0.531 ***	1-4**;3-4**;3-5**
Team token share	minor. 97%	minor. 75%	minor. 100%	minor. 89%	minor. 100%	16.16 *	0.310 **	
Team lockup	single 59%	no 60%	multi. 47%	multi. 78%	no 57%	29.71 ***	0.421 **	1-2**;1-3*;1-4**;2-4**
Pre-sale before ICO	private 69%	no 70%	no 53%	public 56%	no 71%	44.01 ***	0.418 **	1-3***;1-2***;2-4**
Pre-sale discount	yes 100%	no 75%	no 79%	yes 78%	no 71%	43.86 ***	0.723 ***	1-2***;1-3***;1-5***;2-4*;3-4*

Registration needed	yes 93%	no 85%	yes 84%	yes 89%	no 86%	45.58 ***	0.737 ***	1-2***;1-5***;2-3***;2-4**;3-5**;4-5**
Eligibility restrictions	geogr. 55%	none 100%	geogr. 68%	none 56%	none 86%	51.34 ***	0.451 **	1-2***;1-4*;1-5*;2-3***;3-4**;3-5**
Planned occurrence	single 97%	single 50%	single 84%	single 89%	single 57%	20.07 *	0.346 **	1-2**
Purchase limit	none 72%	none 80%	none 79%	min. 44%	none 86%	23.91 *	0.308 **	1-4**;3-4**;2-4**
Sales price	fixed 86%	fixed 75%	fixed 89%	fixed 89%	fixed 57%	4.98	0.243 *	
Price fixing currency	crypto 55%	crypto 70%	fiat 68%	crypto 78%	crypto 100%	13.3 **	0.398 **	
Funding currency	crypto 83%	crypto 95%	crypto 63%	crypto 67%	crypto 100%	9.36	0.334 **	
Funding cap	hard 66%	hard 45%	multi. 74%	multi. 67%	none 71%	41.56 ***	0.406 **	1-3**;1-5**;4-5**
Time horizon	fixed 90%	fixed 70%	fixed 95%	fixed 89%	fixed 71%	8.59	0.226 *	
Auction mechanism	no 97%	no 90%	no 100%	no 100%	no 71%	9.08	0.329 **	
Time based discount	multiple 52%	multiple 55%	no 58%	no 56%	multiple 43%	14.09	0.290 *	

* $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$
a Percentages in one cluster which show a given characteristic
b Threshold ***V >=0.5; **V>=0.3; *V>=0.2
c Post hoc significances between single clusters are tested using Pearson's $\chi 2$

5 Analysis and Implications of ICO Archetypes

The cluster analysis grouped five distinct entities of similar kind with regard to the respective ICO's design characteristics, minimizing the variance within the groups. Due to the initial hierarchical clustering approach, which does not require to pre-specify a number of clusters, our analysis yields in a different number of clusters compared to the archetypes from Fridgen, Regner, Schweizer and Urbach [7]. Additionally, since our dataset also includes novel forms of ICOs, our five clusters differentiate more particularly with regard to the token terms including the token purpose. Each of these clusters thereby form a unique archetype which we investigate in the following.

Archetype 1: The average ICO. This ICO archetype represents the largest cluster. We perceive its characteristics as the most typical ones since it resembles the patterns of a traditional crowdfunding campaign. Based on top of an existing blockchain, the issuer raises a capped amount of funding. Capping the amount possibly avoids being perceived greedy and may mitigate the risk of regulatory attention [57]. A private pre-sale allows the issuer to raise money prior to the regular sale. The team can then focus on developing the product early, whereas the early investors benefit from a discount. This archetype implements a usage token providing access to a service or platform and does not transfer voting rights or company shares to the token holders. It therefore tends to target investors who are interested in the actual use case, i.e. the access to a service or platform provided, rather than e.g. investment returns.

Archetype 2: The liberal ICO. This archetype shows comparably less governance from issuers with regard to sales terms and issuer terms. It tries to maximize the target group of prospective buyers, since it does not require prior registration. Furthermore, it does not impose geographic restrictions nor restrict the access to accredited investors. Additionally, this archetype does not offer any pre-sale and there is no purchase amount limit. This indicates that the tokens are sold on a first-come, first-served basis without favoring wealthy or institutional investors. Thereby, we consider that this archetype corresponds the most to the truly global and inclusive blockchain idea [37]. This archetype partially includes those ICOs planning multiple funding rounds instead of a single round only. In venture capital, funding traditionally takes place in multiple rounds, one consequence is that the issuing team remains incentivized [58]. This is why blockchain experts also believe that an iterative funding approach could be the future of ICOs [59].

Archetype 3: The visionary ICO. In many of its design parameters, this ICO archetype offers several value propositions. The issuer grants voting rights to its investors which can thereby participate in the initiative's development. Additionally, the archetype sets lockup periods for the token share allocated to the issuer. These lockups prevent the team from selling their tokens directly after the closing of the ICO, which stabilizes the post-ICO token price [60]. Further, this archetype specifies both, a soft and a hard cap for the ICO. The announcement of a clear funding target range conveys the message that the issuer intends to raise an amount aligned with the expected costs of network development [57]. In many cases, the whitepaper specifies that all funds are returned to investors if the ICO fails to reach the soft cap [12]. This procedure reduces the investor's risks and indicates that the team links its funding tightly to the development costs. Thus, we conclude that this ICO archetype goes beyond being just a funding mechanism, but targets at investors that truly believe in the business model and its long-term success.

Archetype 4: The compliant ICO. The prevailing pattern in this archetype represents the regulatory orientation of the ICO design. By burning the unsold tokens post-ICO, the issuer keeps the percentages in token allocation between issuer and investors stable. Usually, the token burning benefits the token holders, since it decreases the total number of available tokens, and, consequently, may increase the value of each individual token [61]. However, a controlled appreciation of the token value may attract regulatory attention, since then the token could be considered as a security [62]. Another peculiarity of this archetype is the structuring of the issuing legal entity as foundation. Recently, there has been a trend in the ICO universe to divide the corporate structure into two separate entities, where a foundation runs the ICO, and another entity runs the business operations [10]. This enables the legal separation of the liabilities associated with the ICO. With regard to the sales terms, the issuer has more information and control over the investors as they need to register before they can purchase tokens. Additionally, pre-defined purchase limits restrict the token sale. Limiting the maximum purchase amount can enhance a wider distribution of the tokens, thereby preventing a token concentration of a single investor. A concentrated token share distribution could raise regulatory issues regarding secondary market trading. Thereby, we conclude that the design of this ICO archetype, more than others, takes into account the current regulatory uncertainty and seeks to comply with potential upcoming ICO regulation.

Archetype 5: The native ICO. Differences regarding the technical token terms predominantly characterize this archetype. In particular, the token implementation level represents a striking characteristic of this archetype. Whereas many tokens use the ERC20 token standard from the Ethereum blockchain, this archetype, however, distributes tokens that are native to their own blockchain. These tokens are often referred to as protocol tokens. They may be used as simple currency or might have other use cases, such as a stake to participate in a network. Often, the developers aim to create novel use cases based on these tokens. These innovative features appear to aim at overcoming challenges of existing blockchain solutions such as scalability [39]. Another unique characteristic in this cluster is the uncapped supply of tokens, so all investors are able to buy as many tokens as they desire. We conclude that this archetype comes with interesting specificities especially for blockchain enthusiasts.

Summarizing, we learn that the five archetypes differ from each other with regard to value propositions, target groups, and existing challenges. From an ICO issuer perspective, a key task constitutes the definition of a clear value proposition. This ultimately translates into the respective target group of investors. For example, designing an ICO similar to archetype 3, the visionary ICO, might also attract investors interested and engaged in the further development of the network. Many ICOs incorporate a liberal design, i.e. archetype 2, corresponding to the fundamental idea of the blockchain technology. Implementing a liberal ICO design, however, one might end up having investors exploiting the non-existing restrictions (e.g. money laundering purposes). From an investor perspective, it is of vital importance to know what the objectives of the ICO issuer are to better understand the token prize development. Being interested in the long-term vision, it might make sense to look out for ICOs with designs similar to the archetypes 1 and 3, the average and the visionary ICO. If an investor primarily seeks a promising financial return, investing into compliant ICOs as archetype 4 might be the right way. In that case, the ICO might attract higher regulatory attention due to the token burning that leads to a potential reduction of the investor's risk. Taking the amount of cases within each cluster into account, we observe that most ICOs currently do not consider regulatory issues. This may be due to the novelty of the phenomenon. Partly, the global nature of blockchain applications may make it difficult to consider the regulatory variety across countries. ICO issuers might therefore decide to ignore any regulatory aspects so far. This picture, however, is likely to change since the ICO phenomenon is attracting more attention recently, especially from the regulatory side.

6 Conclusion and Outlook

ICO as a novel funding mechanism represents a promising example of a blockchain use case that recently draws attention in both, research and practice. Although first research projects analyzed specific aspects of the emerging phenomenon, we poorly understand the implications of ICOs yet. Thus, in this research paper, we bridged this research gap and investigated ICOs with regard to their design parameters and focused on the identification as well as qualitative analysis of predominant archetypes. To do so, we first enriched the established taxonomy for ICO design [7] to account for recent developments in the fast evolving blockchain domain. Second, we used the taxonomy's 23 dimensions as clustering variables and conducted a cluster analysis on 84 ICO cases. As a result, we proposed five ICO archetypes which illustrate different combinations and dominant aspects within the ICO design parameters. Further, we examined these clusters and presented a qualitative interpretation for each archetype.

Before emphasizing our contributions to both research and practice, we acknowledge some limitations as well as highlight promising starting points for future research. First, we limited our sampling procedure to ICOs with exhaustive data available to allow for comprehensive structuring according to the taxonomy's dimensions. Second, we used a convenient data sample, which represents a representative share of the total ICO market only. Third, this paper only addresses ICO design parameters, rather than other ICO aspects, which have been examined in traditional crowdfunding literature, such as the business model and industry or the quality of marketing. These aspects should be subject to further research that might help to better understand the ICO phenomenon. Fourth, the ICO market is highly dynamic and most ICO issuers are startups. Thereby, token sale models are constantly evolving, leading to dynamic emergences of novel ICO design patterns. However, we strongly believe that our empirically obtained archetypes comprehensively describe the current ICO market. Finally, it also remains for future research to investigate how the fast developments of blockchain technology influences the future of ICOs.

The theoretical contributions of our research address the research gap in three ways: First, we provide a systematic and comprehensive overview on predominant ICO designs. We suggest five ICO archetypes with different value propositions, target groups, and challenges. The better fitting clustering method and the qualitative discussion and interpretation of the archetypes allow to abstract from single peculiarities of specific ICOs and enable thereby generalizable propositions. We therefore systemize the findings generated by Fridgen, Regner, Schweizer and Urbach [7]. Second, the archetypes extend existing ICO classifications by various aspects and allow for generalizable findings, instead of taking into account single characteristics. Third, we lay the foundation for further research in the area of ICOs. Since the archetypes are theoretically grounded on an existing taxonomy and empirically verified, they provide a more systematic and in-depth perspective on the phenomenon. This will help synthesize research on ICOs and identity promising research avenues.

Besides our theoretical contributions, our research provides practitioners with various backgrounds and perspectives on the ICO phenomenon. First, the classification into predominant archetypes may provide structured guidance for ventures that plan to conduct an ICO. Second, from an investor point of view, the archetypes can lead to more informed and grounded investment decisions. Third, for traditional financial intermediaries, including early stage venture capitalists or crowdfunding platforms, the enriched taxonomy and archetypes may help to characterize potential competitors. Fourth, our approach to structure the heterogeneous ICO market through design archetypes allows to reduce complexity, which may help regulators to perform regulatory tasks more effectively. This ultimately reduces the uncertainty in the market for all participants.

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