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PRODUCT-ORIENTED ASSESSMENT OF THE COMPETITIVENESS OF CRYPTOCURRENCIES BASED ON EXCHANGE DATA

Abstract: The article presents a product-oriented assessment of the competitiveness of cryptocurrencies. Digital assets are viewed as products with interaction funnels, behavioral indicators, and network effects. The study develops an assessment methodology based on user behavior and network dynamics.

Keywords: information technology, data analysis, trading operations, cryptocurrencies, product analytics, competitiveness, composite index, liquidity, volatility.

1. Introduction

Cryptocurrencies have developed into a distinct class of digital assets, supported by dedicated infrastructure and diverse use cases. Traditional market indicators – such as price, market capitalization, and trading volume – primarily reflect liquidity and speculative sentiment, and are insufficient to fully capture a project's competitive positioning. To assess intrinsic consumer value, a cryptocurrency should be conceptualized as a digital product with a lifecycle, user funnel, cohorts, and network effects. Product analytics, in this context, focuses on measurable user journeys, encompassing acquisition, activation, retention, referral, and conversion processes.

Product analytics represents a systematic evaluation of a cryptocurrency as a digital product. It integrates user-behavior metrics, network-effect intensity, and product-lifecycle efficiency into a coherent evidence base. Several methodological challenges complicate measurement and cross-asset comparability. High volatility and speculative cycles can distort perceived quality by artificially inflating short-term activity. Network effects must be inferred from genuine user behavior rather than raw address counts. Therefore, recurring-use signals are tracked to capture sustained value. These include MAU (Monthly Active Users), DAU (Daily Active Users), cohort retention, transaction frequency, and UX (User Experience)–specific metrics such as transaction latency, interface engagement, error rates, and onboarding friction. Additionally, the informational environment, including social media and news, should be evaluated not only for sentiment but also for its impact on user interactions and product-relevant outcomes. Data are inherently fragmented across on-chain activity, exchanges, social platforms, and analytics dashboards, necessitating consistent normalization and aggregation. Sources of bias – including bots, Sybil identities, and incentive campaigns – require robust filtering and cross-validation.

Within this approach, product analytics operationalizes cryptocurrencies through the AARRR (Acquisition, Activation, Retention, Referral, and Revenue) funnel – augmented by cohort analysis and unit-economics modeling. This approach explicitly links fees, throughput constraints, and user-experience parameters to observed behaviors, thereby bridging operational characteristics with engagement outcomes. Heterogeneous data layers are integrated to form a unified behavioral perspective that combines on-chain transactions, off-chain interactions, and information-driven signals. This integration allows for interpretable assessments of competitiveness based on user engagement, retention, depth of use, and persistent network externalities. Bias mitigation relies on anti-bot heuristics, threshold-based quality criteria, and event-study designs with pre- and post-intervention windows and placebo checks.

The scientific focus of this study is the application of product-oriented measurement methodologies to cryptocurrencies. The central problem addressed is the absence of reproducible, price-independent metrics that accurately reflect user value and comparative competitiveness. **The relevance** of this work stems from the increasing importance of data-driven evaluation for digital assets and its role in enhancing market transparency. A product-oriented, reproducible approach disentangles genuine utility from market fluctuations and enables objective, comparable indicators of competitiveness.

2. Literature review and problem statement

Recent studies increasingly conceptualize cryptocurrencies as platform-type digital products, whose utility emerges from user adoption, complementary services, and network externalities. Competitiveness is therefore determined not solely by market quotations but primarily by user behavior along the *acquisition–activation–retention* funnel and by network effects. In product research, validated approaches from HCI (Human-Computer Interaction) and Information Systems support multi-dimensional measurement of user engagement, drawing on systematic reviews of the User Engagement Scale and related constructs. These approaches operationalize indicators such as attention, aesthetics, usability, novelty, and perceived endurance. They can be applied to financial technology contexts, enabling quantification of product-relevant metrics in crypto ecosystems [1]. Empirical studies of network effects and store-of-value properties further indicate that active user scale and composable service structures enhance demand and sustain usage beyond short-term price impulses [2].

The informational layer – comprising news, social media, and search activity – demonstrates systematic associations with returns, trading volumes, and co-movements across assets. Statistically significant effects of sentiment and attention for leading cryptocurrencies justify their use as external predictors of behavioral and product-relevant changes [3]. For example, investor attention measured via the Google Search Volume Index correlates with both cross-sectional returns and trading activity, indicating that attention partially explains differences in asset performance [4]. Common market fluctuations driven by internet attention and sentiment confirm co-movements and shock-transmission channels across digital assets [5].

These findings motivate explicit modeling of attention as a behavioral driver that can precede, amplify, or decay user engagement.

Parallel literature highlights data-quality and bias risks, which directly affect product-level inference. In centralized and decentralized exchanges, wash trading inflates volumes and reduces effective liquidity, distorting derivative product indicators if unfiltered feeds are used [6]. On-chain, mapping from addresses to entities – representing actual users or organizations – is critical for valid adoption metrics. Modern clustering tools, such as BACH (Bitcoin Address Clustering based on multiple Heuristics), reduce biases in active-address counts and align metrics with real users. This improves estimates of adoption, retention, and network interactions [7]. Collectively, these studies underscore the need for measurement designs emphasizing entity resolution, de-duplication, and conservative liquidity proxies.

A complementary research stream examines market microstructure, frictions, and delays in information incorporation into prices. Studies of price delay and realized volatility for Bitcoin and Ethereum document periods of incomplete or lagged information absorption, even in liquid markets [8]. These phenomena relate to interaction costs, order-book depth, and short-term risk faced by users and market makers. They support using friction and liquidity proxies as components of product-oriented indices reflecting trading ease.

At the institutional level, recent reviews propose functional taxonomies of cryptoassets and applications. They support comparable $KPIs$ (Key Performance Indicators) and reduce mismatches between projects with different roles [9]. Syntheses of price-discovery drivers identify multiple channels – including information shocks, liquidity conditions, and institutional features – supporting multi-layer modeling where product, information, and market indicators are jointly analyzed [10]. A macroeconomic view of “trust at scale” outlines economic limits for proof-of-work and proof-of-stake systems. It highlights off-protocol trust infrastructure and warns against attributing all persistent use to product utility [11].

Methodologically, event-study literature in cryptocurrencies codifies standards for measuring short-term effects of announcements and news, recommending pre- and post-event windows, market-factor controls, and heterogeneity analysis across assets or regimes [12]. This framework distinguishes transient marketing or information shocks from persistent behavioral changes. It connects the information layer with product metrics by testing whether attention spikes lead to repeated interactions.

Research formalizing publication analysis and expert forecasts shows the feasibility of converting unstructured texts and opinions into measurable predictors. These can be linked to later usage, adoption, and retention [13–14].

Collectively, the literature suggests three complementary axes for evaluating cryptocurrency competitiveness as digital products:

– Information impulses: attention and sentiment derived from news, search, and social media [3–5];

– Market microstructure and frictions: data quality, transaction costs, and short-horizon risk [6, 8];

– User-product behavior: network effects and engagement measured at the entity level and normalized across functional classes [1–2, 7, 9].

The principal gap lies in reproducible empirical designs that integrate these axes into a unified behavioral positioning framework with transparent normalization and interpretable weighting. The present study addresses this gap by aggregating product metrics into a composite index and treating information signals and market frictions as external control factors within a unified comparative methodology.

The next section specifies the aim, object, and subject of the study, alongside the main research objectives, highlighting the scientific novelty and practical significance of the proposed approach.

3. The aim and objectives of the study

The aim is to develop an approach for product-oriented assessment the competitiveness of cryptocurrencies. A cryptocurrency is treated as a digital product with an interaction funnel, behavioral metrics, and measurable network effects. This perspective shifts evaluation from traditional market indicators toward behavioral and product indicators that reflect actual consumer value and quality of use.

To accomplish this aim, the study pursues the following **objective**:

– To develop an integrated methodology of product-oriented analytics to determine the competitiveness of cryptocurrencies. This methodology combines user behavior indicators (active users, retention, transaction frequency, UX parameters), network effects, and information signals (social networks, news, search queries) into a single competitiveness index.

4. The study materials and methods for assessing product-based competitiveness of cryptocurrencies

Having defined the purpose and subject of the study, we provide a detailed description of the methods used. They were used to construct the Product Competitiveness Index (PCI) and formalize behavioral and product indicators.

4.1. General description of the study

This study addresses three tightly connected questions within a product-analytics approach for cryptocurrencies. The first asks which product indicators best distinguish strong projects from weak ones relative to traditional market variables. The second examines whether social-media publications are associated with product-relevant shifts in the usage funnel rather than only short-lived price reactions. The third tests whether a reproducible composite indicator remains stable across time and robust to plausible weighting choices.

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The working hypothesis has three components that guide the design. Adoption and retention metrics provide higher discriminative power than price or capitalization for ranking product strength. Attention and tone shocks in the information environment correlate with short-term activation and conversion, but do not guarantee long-term retention. A normalized composite, constructed from product-layer metrics, can separate core assets from noise consistently across subperiods and weighting schemes.

The empirical design proceeds in a structured sequence aligned with the journal's methods requirements. We first define and operationalize product-relevant features that reflect user journeys and network dynamics. We then collect, clean, and standardize data, compute indicators for the selected assets, and construct a composite index of product competitiveness with transparent weighting. Finally, we form a coherent ranking and explain the underlying factors that drive positions. These steps ensure reproducibility, comparability, and interpretability.

Operationalization covers several behavioral layers consistent with product analytics. Adoption and activation are measured by new users and transitions to a first transaction within an observation window. Retention and engagement capture recurrence, action frequency, and the depth of purposeful interactions across sessions. Network scale reflects the size of the active base, the count of unique counterparties, and the breadth of interactions with decentralized applications. Cost and accessibility summarize the fee burden relative to a representative ticket size, service uptime, and resilience to incidents. Derived indicators include repeat-use share and audience stickiness to capture habit formation.

To support cross-asset comparability, all indicators are standardized and oriented in a "useful" direction. The composite index emphasizes retention and activation as the core of consumer value. Secondary emphasis is placed on network intensity and interaction depth, followed by cost and reliability dimensions. Sensitivity is evaluated by varying the weight vector across a grid and by using alternative normalization schemes. When helpful, a weight-free Pareto selection in the space of persistence, stability, and interaction intensity is also reported.

The sample consists of five liquid assets with reliable coverage: BTC (Bitcoin), ETH (Ethereum), DOGE (Dogecoin), SOL (Solana), and BNB (Binance Coin). The study window spans January-July 2025, during which order flow, trade counts, and quote volumes are well documented. Exchange data are taken from minute bars and trade journals on a major centralized venue. On-chain data provide transfers, contract calls, and, where feasible, unique counterparties inferred from address clustering. The social layer is represented by publications on X (former social network Twitter), which supply time-stamped attention and tone features.

Data quality is addressed through several safeguards that reduce known biases. Address-level signals are mapped to entities, when possible, to approximate users or organizations and to limit artificial inflation. Anti-bot filters and minimum-activity thresholds remove non-economic traffic from behavioral aggregates. Trading venues with suspicious volume patterns are excluded from quoted-volume totals. Cross-chain normalization accounts for differences in fee regimes and user-experience constraints that affect interaction costs.

Validation follows the journal's emphasis on reproducibility and robustness. Rankings are recomputed on rolling subperiods to evaluate temporal stability. Weighting robustness is assessed by perturbing the baseline weights within a $\pm 20\%$ envelope and comparing rank correlations. External adoption proxies are used for cross-checks of direction and approximate magnitude. An event-study framework evaluates information shocks on X within short pre- and post-windows while controlling for market background. The focus shifts from prices to product-relevant changes in activation, conversion, and retention.

The expected outcome is a reproducible product competitiveness index with interpretable factor contributions. We anticipate a consistent asset ordering and practical positioning maps that support targeted recommendations. These recommendations address cost of use reduction, time to activation improvements, expansion of network breadth, and durable retention across market regimes. The methodology aims to inform product strategy and monitoring in crypto ecosystems while remaining independent of absolute price levels.

The object of the study is the formation and evaluation of cryptocurrency competitiveness based on user behavior, product characteristics, and network dynamics. The subject comprises methods, indicators, and analytical models for product-based assessment of cryptocurrencies. We focus on reproducible proxy metrics: persistence of active days, stability of volume flow, intensity of micro-interactions, effective interaction cost, Amihud-type illiquidity, daily realized volatility, and an accessibility indicator. These features are integrated into a composite PCI that enables comparative positioning irrespective of price levels.

The practical value is a methodological basis for shifting decision-making from price indicators to behavioral metrics in positioning, development, and management of cryptocurrency products. The approach supports product analytics for crypto projects, financial research, and monitoring systems for crypto-ecosystems. It improves the precision of competitive diagnostics, reveals user-engagement dynamics, and informs growth strategies under differing market conditions and infrastructure constraints.

In this study, a methodology is proposed to determine the competitiveness of selected assets, which involves ranking them based on the values of the PCI. It involves ranking them based on PCI values calculated using the linear convolution method. For this purpose, six product metrics were selected, the values of which will be the parameters of the method. The values of the selected parameters were calculated based on input statistical data obtained from the crypto exchange. The weights of each parameter were set by the authors of the article, considering their importance for assessing the quality of assets. Based on the obtained PCI values, each asset was ranked. This was done to select cryptocurrencies for further research on the impact of posts by famous people on social networks on their exchange rate. The steps within this methodology are described in more detail in section 4.4.

Based on the above, it is appropriate to move on to the formal formulation of the task specified in section 3. This allows for the systematic integration of behavioral and product metrics into a single composite competitiveness index and ensures the accuracy and reproducibility of the assessment of crypto assets.

4.2. Formal problem of PCI calculation statement

Prevailing assessments of cryptocurrency competitiveness rely on market variables such as capitalization, price, trading volume, and liquidity. These measures largely reflect speculative sentiment and trading conditions rather than genuine consumer value. They do not capture persistence of user interactions, depth of engagement, or behavioral dynamics of crypto ecosystems across regimes.

To address this limitation, we adopt a product-oriented assessment that treats a cryptocurrency as a digital product with a usage funnel, cohort structure, and measurable network effects. Within this perspective, evaluation must shift from price-based quantities to behavioral and product metrics that reflect sustained use and quality of experience. These metrics are then integrated into a single, comparable indicator suitable for cross-asset benchmarking and longitudinal monitoring.

The study therefore develops a composite PCI that satisfies four requirements consistent with scientific reproducibility. The index uses min–max normalization within the study window and an interpretable system of weights. It incorporates behavioral proxy metrics capturing activity persistence, stability of volume flow, interaction intensity, effective interaction cost, Amihud-type illiquidity, realized volatility as a risk proxy, and network availability. It enables comparisons of cryptocurrencies independent of absolute price levels or capitalization. Finally, it supports an interpretable behavioral picture of competitiveness rather than a purely financial snapshot.

Solving this problem improves precision in diagnosing the state of crypto ecosystems and enables routine monitoring of product development for digital assets. It provides a practical basis for strategic decisions on positioning, roadmap priorities, and evaluation of investment attractiveness grounded in observable user behavior.

The empirical setting is defined to ensure transparency and repeatability. Minute bars from Binance Spot against a dollar-denominated stable asset are aggregated to daily and monthly indicators for January to July 2025. All timestamps are aligned to Coordinated Universal Time. Extreme observations are treated via winsorization of the top one to two percent by volume or event frequency. Trading venues or intervals that exhibit artificial volume patterns are excluded from the quoted-money volume aggregates $Q_{i,t}$ used in downstream calculations.

An event file documents downtime and technical constraints on deposits or withdrawals to control for exogenous outages. For the social layer, we construct an information influence index $INF_{i,t}$. The index is a normalized combination of daily mentions and sentiment, where $sentiment \in [-1; 1]$. Days with $INF_{i,t}$ above the ninety-fifth percentile for asset iii are flagged as information shocks. When entity-level on-chain data are available, they are used to cross-check exchange-based proxies of activation, repeat use, and audience stickiness.

These design choices translate a descriptive problem into an operational one with explicit inputs, outputs, and quality safeguards. Orientation "toward usefulness", normalization, and weighting rules are specified ex ante to reduce researcher degrees of freedom. The resulting framework targets robustness across subperiods and stability under alternative parameterizations.

To implement the methodology rigorously, we now move from the substantive statement to the mathematical formulation. The next subsection defines variables, aggregation rules, normalization, and the computation of the PCI for a set of cryptocurrencies.

4.3. Mathematical formulation of the problem of PCI calculation

Let S be a set consisting of n cryptocurrencies, indexed by $i = 1, \dots, n$.

Using statistical data for these cryptocurrencies, we compute k product-proxy metrics indexed by $j = 1, \dots, k$. The indicators are: PDA (Product-Driven Activity), SV (Search Volume), TI (Transaction Intensity), $ILLIQ$ (Illiquidity Ratio), ECP (Effective Conversion Performance) and UR (User Retention). The indicators are represented as a $k \times n$ matrix $X = \{x_{i,j}\}$, where $x_{i,j}$ – is the raw value of indicator j for asset i.

As the output, based on the calculated indicators, we obtain the value of the PCI for each of the n cryptocurrencies.

For practical implementation of the composite index, the key metrics must be specified and formalized prior to aggregation. Each indicator requires a clear definition of its measurement domain, units, and time aggregation rules. Daily observations are aggregated to monthly statistics using robust summaries that reduce the influence of extreme values and episodic shocks. Period values correspond to medians across months within January–July 2025.

The matrix X thus serves as the standardized input layer for index construction. Subsequent steps include orientation toward usefulness, $min - max$ normalization within the study window, and weighting according to the methodological priorities stated earlier. The final composite is computed for each asset and used for ranking, stability analysis, and interpretation of factor contributions.

To determine the integral index of product competitiveness, the methodology of its calculation must be detailed in the following section.

4.4. Methodology to determine the competitiveness of cryptocurrencies

To solve the problem, the following steps must be taken:

STEP 1. Identify and formalize a system of product competitiveness indicators for cryptocurrencies, including the above-mentioned metrics.

STEP 2. Calculate the PCI based on $min - max$ normalization and the linear convolution method, taking into account the weighting coefficient system. PCI takes into account the relationships between behavioral and network characteristics of assets.

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STEP 3. Empirically test the proposed model on major cryptocurrencies representing diverse tokenomic frameworks – PoW (Proof of Work), PoS (Proof of Stake), DeFi (Decentralized Finance), utility, and stablecoins. This will allow assessing its effectiveness, robustness, and sensitivity to market fluctuations and behavioral variations.

STEP 4. Interpret the assessment results in the context of product competitiveness, identify clusters of cryptocurrencies by level of behavioral stability, and determine the factors that determine their market advantage.

The sequence of steps in the proposed methodology is shown in Fig. 1.

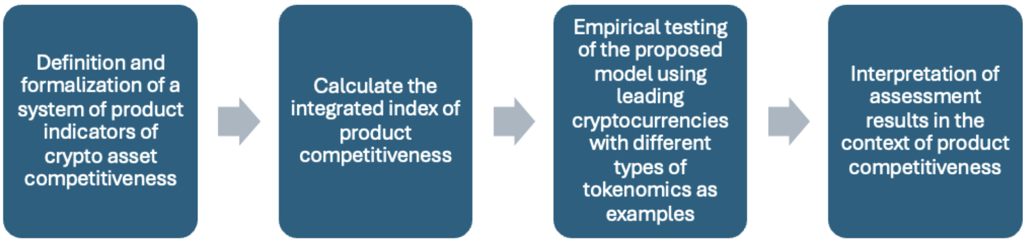

Figure 1. PCI calculation methodology diagram

After outlining the competitiveness index, the next section defines each product proxy metric and details the daily, monthly, and period-based aggregation used in building the composite indicator.

4.5. Product-proxy metrics

For asset $i \in S$ and day t, denote daily Open, High, Low, Close and Volume as $H_{i,t}$, $L_{i,t}$, $C_{i,t}$, $V_{i,t}$. Let $N_{i,t}$ be the number of trades, $TB_{i,t}$ – the "aggressive buy" volume, $Q_{i,t}$ – the quoted money volume in USDT (United States Dollar Tether).

Daily log-return is calculated using formula (1):

$$r_{i,t} = ln\left(\frac{C_{i,t}}{C_{i,t-1}}\right). \tag{1}$$

Relative daily range is calculated using formula (2):

$$rcp_{i,t} = 2 \cdot \frac{H_{i,t}-L_{i,t}}{H_{i,t}+L_{i,t}}. \tag{2}$$

Trade intensity (trades per minute) is calculated using formula (3):

$$TI_{i,t} = \frac{N_{i,t}}{1440}. \tag{3}$$

Buy-flow share is calculated using formula (4):

$$TBR_{i,t} = \frac{TB_{i,t}}{V_{i,t}}. \tag{4}$$

Realized intraday volatility from minute prices $p_{i,\tau}$ within day t is calculated using formula (5):

$$rv_{i,t} = \sqrt{\sum_{\tau \in t}\left(ln\left(\frac{p_{i,\tau}}{p_{i,\tau-1}}\right)\right)^2}. \tag{5}$$

Amihud-type illiquidity as price impact per unit of money volumeis calculated using formula (6):

$$ILLIQ_{i,t} = \frac{|r_{i,t}|}{Q_{i,t}}. \tag{6}$$

Monthly aggregation uses medians or means of daily values within month m. Here Me, denotes the sample median and D_m the number of days in month m.

Intensityis calculated using formula (7):

$$TI_i^m = Me_t(TI_{i,t}). \tag{7}$$

Share of "active" days is calculated using formula (8):

$$PDA_i^m = \frac{1}{D_m} \sum_{t \in m} \gamma_{i,t}, \tag{8}$$

where $\gamma_{i,t} = \begin{cases} 1, N_{i,t} \geq Me(N_{i,t}); \\ 0, N_{i,t} < Me(N_{i,t}). \end{cases}$

Stability of volumes is calculated using formula (9):

$$SV_i^m = \frac{\overline{Q_{\iota,m}}}{\sigma(Q_{i,m})}, \tag{9}$$

where $\overline{Q_{\iota,m}}$ – is the sample mean of monthly quoted volumes and, $\sigma(Q_{i,m})$ – the sample standard deviation.

Flow balance is calculated using formula (10):

$$TBR_i^m = \frac{\sum_{t \in m} TB_{i,t}}{\sum_{t \in m} V_{i,t}}. \tag{10}$$

Average daily volatility is calculated using formula (11):

$$RV_i^m = Me_t(rv_{i,t}). \tag{11}$$

Illiquidity is calculated using formula (12):

$$ILLIQ_i^m = Me_t(ILLIQ_{i,t}). \tag{12}$$

Relative range is calculated using formula (13):

$$RCP_i^m = Me_t(rcp_{i,t}). \tag{13}$$

Let the fee parameter TFA (Transaction Fee Adjustment) be fixed for all assets in the period.

Effective interaction cost is calculated using formula (14):

$$ECP_i^m = RCP_i^m + TFA. \tag{14}$$

Network availability is calculated using formula (15):

$$UR_i^m = 1 - \frac{d_{i,m}}{h}, \tag{15}$$

where $d_{i,t}$ – is monthly downtime and h – the number of minutes in the month. Availability is obtained from an incident calendar; if no incidents are recorded, set $UR_i^m = 1$.

Period summary for January-July 2025 uses medians of monthly values cost is calculated using formula (16):

$$K_i^{per} = Me_m(K_i^m), \tag{16}$$

for $K \in \{TI, PDA, SV, TBR, RV, ILLIQ, RCP, ECP, UR\}$.

To align scales, we apply $min - max$ normalization in the “useful” direction and invert “lower is better” indicators (formulas (17), (18)):

$$iILLIQ_i = \frac{1}{ILLIQ_i^{per}}, \quad (17)$$

$$iECP_i = \frac{1}{ECP_i^{per}}. \quad (18)$$

After defining and normalizing individual product-proxy metrics, the next step aggregates them into a single composite competitiveness measure. The measure jointly reflects persistence of engagement, interaction intensity, frictions, and network availability for each asset.

4.6. Aggregation and the composite index

The composite PCI_i is calculated using formula (19) as the weighted sum of normalized features for the study period [15]:

$$PCI_i = w_1 \cdot \widetilde{PDA}_i + w_2 \cdot \widetilde{SV}_i + w_3 \cdot \widetilde{TI}_i + w_4 \cdot \widetilde{iILLIQ}_i + w_5 \cdot \widetilde{iECP}_i + w_6 \cdot \widetilde{UR}_i, \quad (19)$$

here «~» denotes $min - max$ normalization across assets within the period, applied after orientation toward usefulness.

Weight profile:

$$w_1 = 0.25;\ w_2 = 0.2;\ w_3 = 0.15;\ w_4 = 0.15;\ w_5 = 0.15;\ w_6 = 0.1.$$

$$\sum_{k=1}^{6} w_k = 1.$$

The choice of this method is justified by its simplicity, convenient scalability, speed of calculation, and intuitive clarity.

The profile prioritizes engagement persistence and volume stability, assigns secondary weight to interaction intensity and friction measures $iECP$ and $iILLIQ$, and further considers network availability.

This configuration encodes a product-oriented stance. Retention and stable flow signal durable value; intensity captures depth of use; friction and availability reflect cost and reliability perceived by users. Normalization ensures commensurate scales and prevents any single metric from dominating due to units.

Robustness checks. Index robustness is tested by varying the weight vector within a $\pm 20\%$ envelope and by applying alternative normalization schemes. Rank correlations across scenarios evaluate stability of comparative positioning. As a weight-free diagnostic, we also compute a Pareto selection in the space $(PDA, SV, TI, 1/ECP)$. Assets on the frontier remain efficient without assuming any specific weights.

Interpretation. The index value summarizes product competitiveness for each asset over January-July 2025.

Having specified the aggregation rule and validation protocol, we now present the empirical results, examine ranking stability, and interpret factor contributions within a product-competitiveness perspective.

5. Results of investigating cryptocurrency product-based competitiveness

This section presents empirical results from applying the proposed methodology to major cryptocurrencies with distinct tokenomic frameworks – PoW for BTC, PoS for ETH, SOL, and BNB, and meme coin DOGE. The analysis combines behavioral, transactional, and friction indicators to assess product-based competitiveness across assets.

5.1. Descriptive summaries by asset

Aggregating minute series to daily values, then to monthly statistics, and finally to medians over the whole window produces a clear stratification. BTC exhibits the highest density of micro-interactions and the most persistent activity together with a low cost of use and restrained short-horizon risk. ETH trails BTC on interaction density and persistence, yet shows a more stable flow of quoted volumes, at the cost of higher frictions and higher realized volatility. SOL shows mid-level interaction intensity with elevated stability and a higher effective cost. BNB delivers the lowest cost and the lowest volatility, but also the lowest density and persistence. DOGE combines moderate density and persistence with the highest effective cost and the highest realized volatility. These patterns are summarized in Table 1 and align with the qualitative ranking discussed later.

Before computing the composite index, we keep units explicit. TI denotes trades per minute. PDA measures the share of "active" days as defined in Section 4.5. SV summarizes volume-flow stability. TBR (Trade Buy Ratio) reports the buy-flow share. RV (Realized Volatility) captures average daily realized volatility. $ILLIQ$ is Amihud-type illiquidity; we report $ILLIQ \cdot 10^{-10}$ for readability. RCP (Relative Closing Price Range) is the relative daily range. TFA is the fixed fee parameter. ECP is the effective interaction, where $cost = RCP + TFA$. UR measures network availability.

As expected, BTC's high TI and PDA coincide with low ECP and moderate RV, indicating frequent, persistent use at low frictions and tolerable short-horizon risk. ETH shows similar behavioral strength but higher frictions and volatility, consistent with a richer execution environment and congestion costs. SOL's elevated SV suggests steady order flow, but ECP remains higher than for BTC and BNB. BNB's very low ECP and RV imply a smooth user experience, albeit with lower interaction intensity. DOGE's high ECP and RV indicate costly, riskier usage despite moderate activity levels.

Table 1.

Raw monthly medians (01–07.2025), (matrix X)

Symbol	TI	PDA	SV	TBR	RV	$ILLIQ$	RCP	TFA	ECP	UR
BTC	2258.75	0.581	1.711	0.489	0.0250	0.065	0.0322	0.001	0.0332	1.0
ETH	2110.71	0.548	1.788	0.494	0.0384	0.151	0.0500	0.001	0.0510	1.0
SOL	1447.53	0.516	1.855	0.492	0.0470	0.476	0.0640	0.001	0.0650	1.0
BNB	540.95	0.452	1.908	0.505	0.0214	0.670	0.0277	0.001	0.0287	1.0
DOGE	746.83	0.484	1.605	0.486	0.0498	1.100	0.0647	0.001	0.0657	1.0

These descriptive results motivate feature orientation and $min - max$ normalization to a commensurate scale. Normalization prevents unit effects from biasing weights and prepares inputs for the composite index. It also supports transparent contribution analysis by keeping feature magnitudes within a common range.

Based on these raw medians, the next subsection applies $min - max$ normalization and computes the composite product competitiveness index, followed by stability checks and interpretation of factor contributions.

5.2. Feature normalization and computation of PCI

We apply $min - max$ normalization "toward usefulness" to each oriented feature. Normalization is computed across assets within the study window. It produces commensurate scales for aggregation and contribution analysis.

Network availability $UR = 1$ for all assets in our sample. We therefore report UR for completeness, but it adds a constant offset and does not affect ordering. Keeping the constant term preserves alignment with Section 4.6 and facilitates contribution tracing.

Table 2 presents normalized features and the composite index. The values reflect medians over January-July 2025 after orientation and normalization.

Table 2.

Normalized features ($\boldsymbol{min - max}$)

Symbol	$\boldsymbol{Norm\ PDA}$	$\boldsymbol{Norm\ SV}$	$\boldsymbol{Norm\ TI}$	$\boldsymbol{Norm\ iILLIQ}$	$\boldsymbol{Norm\ iECP}$	$\boldsymbol{Norm\ UR}$
BTC	1.00	0.350	1.000	1.000	0.760	1.0
ETH	0.75	0.605	0.914	0.396	0.225	1.0
SOL	0.50	0.825	0.528	0.083	0.009	1.0
BNB	0.00	1.000	0.000	0.041	1.000	1.0
DOGE	0.25	0.000	0.120	0.000	0.000	1.0

Fig. 2 visualizes the normalized feature composition by asset. The chart confirms the descriptive patterns from Section 5.1 and highlights the dominant drivers for top ranks.

For transparency, we decompose the index into weighted components $w_k \cdot \widetilde{x_{ik}}$ for each feature k.

Summing these components exactly recovers the reported PCI_i.

The decomposition isolates factor influence by asset, making relative contributions visible rather than latent.

Large terms such as $0.25 \cdot \widetilde{PDA_i}$ or $0.15 \cdot \widetilde{iECP_i}$ indicate primary drivers of competitiveness.

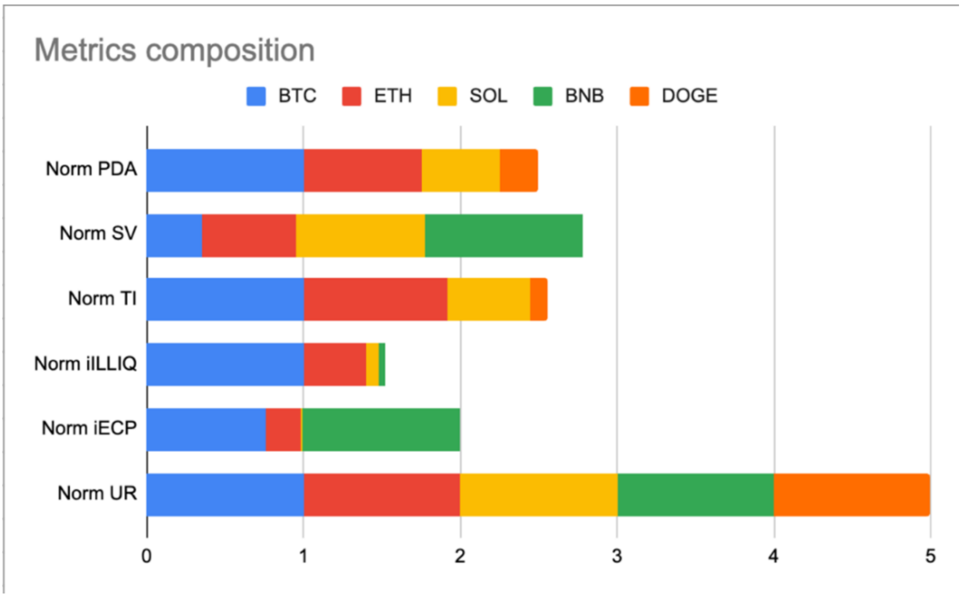

Figure 2. Comparison of normalized product metrics by asset (metrics composition)

Near-zero components flag bottlenecks: for example, low TI_i or $\widetilde{\iota ILLIQ_\iota}$ depress the composite despite strengths elsewhere.

Because all $\widetilde{x_{\iota k}} \in [0,1]$ and $w_k \geq 0$, contributions are non-negative and directly interpretable as share-like addends.

A constant feature, such as $UR_i = 1$, shifts all indices equally and leaves ordering invariant, while still aiding reconciliation with the weighting scheme. As shown in Table 3, the weighting scheme translates these normalized feature values into directly comparable component contributions.

Table 3.

Decomposition of PCI_i into weighted feature contributions

Symbol	$\widetilde{PDA_\iota}$	$\widetilde{SV_i}$	$\widetilde{TI_i}$	$\widetilde{ILLIQ_i}$	$\widetilde{ECP_\iota}$	PCI_i
BTC	0.250	0.070	0.150	0.150	0.114	0.834
ETH	0.188	0.121	0.137	0.059	0.034	0.639
SOL	0.125	0.165	0.079	0.012	0.001	0.483
BNB	0.000	0.200	0.000	0.006	0.150	0.456
DOGE	0.063	0.000	0.018	0.000	0.000	0.180

Key observations follow directly from Tables 2 and 3. The top two positions arise from high persistence and intensity for BTC and ETH, amplified by low frictions and lower illiquidity for BTC. Third and fourth positions reflect trade-offs. SOL maintains better intensity and persistence than BNB but is penalized by higher interaction cost. BNB benefits from maximum stability and low cost yet loses ground on activity density. DOGE ranks last due to high frictions and risk alongside only moderate activity.

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Fig. 3 shows monthly medians of the composite index over the study window. The trajectories are stable, with BTC and ETH consistently ahead, and SOL and BNB alternating within the middle tier.

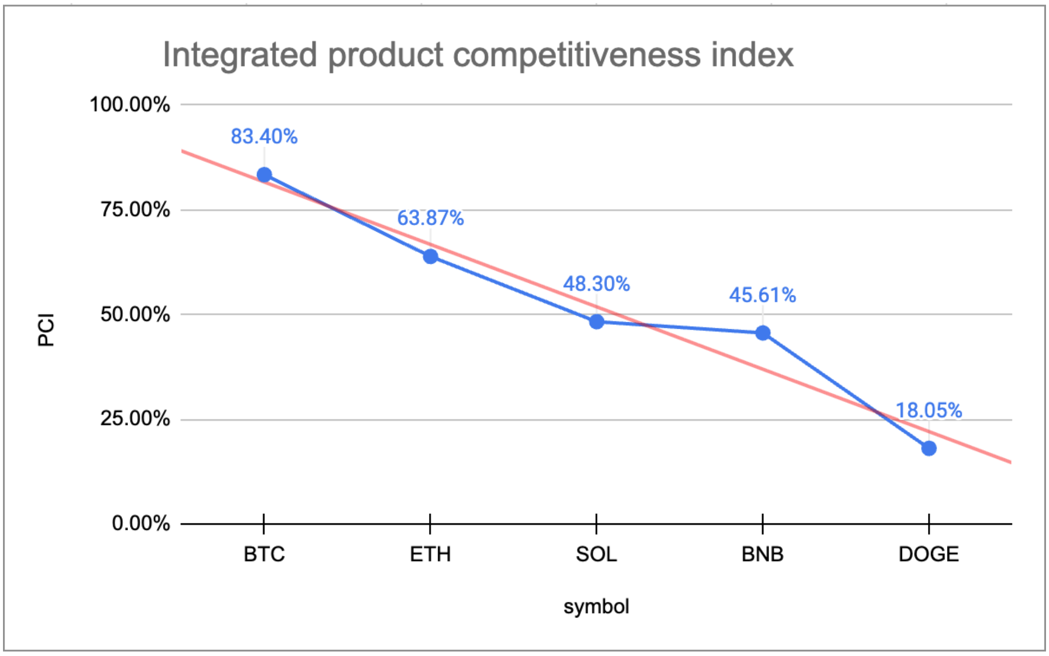

Figure 3. Composite product competitiveness index PCI
by month, 01-07.2025 (monthly medians)

With normalized features and index values established, the next subsection examines stability across subperiods, tests robustness to alternative weight schemes, and discusses implications for product positioning.

5.3. Final positioning and ranking

Position on the efficiency frontier is determined by joint optimization along two axes. The first axis is persistence and intensity of interaction, captured by PDA and TI. The second axis is low transactional frictions, proxied by $1/ECP$, supported by flow stability SV. Under this logic, the consistent ranking for January-July 2025 is BTC–ETH–SOL–BNB–DOGE.

The contribution breakdown in Table 3 shows that final placement is never produced by a single metric. For BTC, the largest shares come from high PDA and TI combined with low frictions and low illiquidity. For ETH, performance reflects a balanced mix of PDA, TI, and SV, offset by higher effective cost. For SOL, the bottleneck is the interaction-cost component; otherwise, activity and stability are competitive. For BNB, the deficit lies in interaction density and persistence despite favorable cost and volatility. For DOGE, elevated frictions and risk depress the index even with moderate activity.

Fig. 2 helps visualize how these components interact on a normalized scale. BTC dominates the PDA and TI bars while maintaining strong $\iota\widetilde{ECP_{\iota}}$ and $\iota\widetilde{ILLIQ_{\iota}}$. ETH posts broad but shallower bars, consistent with a balanced profile under congestion-sensitive costs. SOL's profile is mid-range on activity with a short cost bar, confirming the penalty from ECP. BNB shows long cost and stability bars, but short activity bars. DOGE exhibits short cost and liquidity bars together with only moderate PDA and TI.

Monthly trajectories in Fig. 3 support the cross-sectional ordering. BTC and ETH maintain leads across months with narrow variability bands. SOL and BNB alternate within the middle tier depending on cost and realized volatility conditions. DOGE remains persistently below the frontier, indicating structural frictions rather than temporary shocks.

These results yield a clear map of relative strengths and weaknesses by asset. The PCI ranking integrates engagement, interaction intensity, flow stability, and frictions into an interpretable measure. The index highlights actionable levers: reduce ECP for SOL, raise PDA and TI for BNB, and address cost and risk drivers for DOGE. For BTC and ETH, preserving low frictions while maintaining recurrent use appears central to sustaining advantage.

The following section defines the scientific novelty of the results obtained.

5.4. Scientific novelty of the results obtained

The scientific novelty lies in adapting product-analytics methodologies to the specific conditions of the cryptocurrency market. A composite PCI is proposed, integrating normalized behavioral, transactional, and UX-based indicators to evaluate crypto products independently of price or capitalization. The study demonstrates, for the first time, that persistence, flow stability, interaction intensity, liquidity, and friction metrics can serve as product-oriented measures of competitiveness in digital assets.

6. Discussion of the research results

As mentioned above (in particular in section 5), the competitiveness of cryptocurrencies as digital products is being studied using product analytics that combines behavioral, transactional, and UX metrics. The following aspects were identified in the analysis.

6.1. Interpretation in product-analytics coordinates

Behavioral interaction – approximated here by micro-interaction density and persistence of active days – emerges as the primary layer that separates assets by “quality of use”. Bitcoin shows the highest values ($TI \approx 2258.8$ trades per minute; $PDA \approx 0.581$). Ethereum ranks second ($TI \approx 2110.2$; $PDA \approx 0.548$). This pattern aligns with a “stickiness” interpretation at the trading interaction level. All else equal, frequent and regular micro-interactions with the order book correlate with deeper product utility and habit formation.

Solana exhibits mid-range TI with respectable persistence, indicating repeated, but cost-sensitive, usage. BNB underperforms specifically on interaction intensity despite low frictions, with $TI \approx 541.0$ and $PDA \approx 0.452$. Dogecoin sits in the middle on TI/PDA ($\approx 746.8/0.484$), yet frictions and risk offset these behavioral signals. Together, these outcomes confirm that activity intensity and persistence are necessary but not sufficient conditions for competitive strength.

Interaction frictions are interpreted as a daily "price of use". Minimal ECP for BNB (≈ 0.0288) confers a product advantage: users can rebalance or interact cheaply. Maximum ECP for DOGE (≈ 0.0658) raises barriers to repeated operations and discourages marginal usage. BTC and ETH occupy moderate ECP levels (≈ 0.0333 and ≈ 0.0510), which, when combined with high TI/PDA, yield a favorable utility to cost balance.

A microstructure dimension, $ILLIQ$ – is naturally lower for large-cap assets. After orientation in the "useful" direction $1/ILLIQ$, it still strengthens BTC/ETH positions relative to smaller tokens. The mechanism is direct: lower price impact per unit of money volume reduces effective cost and improves user experience during order execution.

SV reflects evenness of volume streams and matters for "predictable" costs and liquidity. The highest SV values are observed for BNB and SOL (≈ 1.91 and ≈ 1.85), while DOGE is lower (≈ 1.61), consistent with a more "spiky" dynamic. However, equalized flow alone does not guarantee a strong composite outcome. Without sufficient interaction intensity (TI and PDA), it tends to indicate a "stable yet shallow" level of engagement.

Short-horizon risk is highest for DOGE (≈ 0.0498) and lowest for BNB (≈ 0.0214). Practically, repeated usage for DOGE is costlier and less predictable, whereas BNB delivers a calmer experience at low ECP. Flow balance oscillates near symmetry: BNB shows a mild buy-flow dominance (≈ 0.505), while BTC/ETH hover near 0.49. Differences in TBR did not drive the final ordering.

In summary, the product positioning architecture is as follows. BTC leads through the combination of persistent interaction and low frictions and illiquidity. ETH maintains second place due to a balance of stable flow and high TI/PDA, despite higher ECP. SOL occupies the middle because of larger frictions under otherwise decent stability. BNB compensates with cost and risk advantages yet lacks interaction intensity. DOGE remains structurally disadvantaged by the joint impact of high frictions and elevated risk amid only moderate engagement.

This behavioral-and-microstructure reading clarifies which aspects of user interaction confer advantage. It also identifies actionable levers: reduce ECP for SOL, boost TI/PDA for BNB, and lower cost and risk drivers for DOGE. BTC and ETH should preserve low frictions while maintaining recurrent use to sustain their lead.

The next subsection aligns these observations with the initial hypothesis and the computed PCI, assessing how product analytics maps onto the aggregate competitiveness ranking.

6.2. Alignment with the hypotheses and the PCI index

The hypothesis that product proxies outperform pure market variables is supported. The ordering by PCI diverges from trivial rankings by price or capitalization. PDA, SV, and frictions (ECP, $1/ILLIQ$) carry decisive weight.

The weight profile – prioritizing PDA and SV, then TI and friction proxies – penalizes low interaction despite cheap execution, as seen for BNB. It also penalizes high cost and risk under moderate activity, as seen for DOGE.

Monthly trajectories indicate that medians over January-July 2025 yield a consistent order without sharp month-to-month reversals. This pattern indirectly supports reproducibility of PCI on subperiods. Rank correlations under alternative normalizations and weight envelopes further suggest robustness.

Decomposition tables confirm transparent attribution. Each feature's contribution $w_k, \widetilde{x_{ik}}$ maps directly to interpretable product levers. High PDA/TI can be offset by costly interaction, while strong cost metrics cannot compensate for persistently weak engagement.

Despite alignment with hypotheses, limits warrant caution. Data sources are partly heterogeneous and imperfectly synchronized across chains and venues. Several indicators are proxies rather than direct measurements of user intent or utility.

The study window is limited to seven months, which constrains inference about regime changes. Survivorship and selection biases may remain, even after excluding suspicious venues and winsorizing extremes. Entity resolution reduces address inflation but is not error-free.

Information shocks from social network X are measured by mentions and sentiment; alternative attention measures may yield different amplitudes. The constant availability metric ($UR = 1$) contributes no cross-sectional signal and could be omitted without affecting ranks.

External validity is strongest for highly liquid assets with similar exchange coverage. Extensions should include broader asset sets, longer horizons, and protocol-level measures of throughput and congestion. Event windows can be augmented with placebo calendars and alternative factor controls.

Unlike conventional market measures, the core of the analysis is formed by exchange-derived proxies of product usage: PDA, SV, TI, ECP, and $ILLIQ$, complemented by RV and UR. A cross-section of five major assets (BTC, ETH, SOL, BNB, DOGE) for 01–07.2025 shows the indicators effectively discriminate "strong" from "weak" products without relying on price or capitalization. In this window, the Integral Product Competitiveness Index – constructed via $min - max$ normalization with transparent weights – yields a stable ranking: BTC>ETH>SOL>BNB>DOGE.

Bitcoin leads due to high PDA/TI and low frictions. Ethereum ranks second, balancing flow stability and interaction despite higher costs. Solana and BNB display distinct friction–intensity trade-offs. Dogecoin lags from high frictions and volatility with only

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moderate interaction. This positioning aligns with a product interpretation of “use-value”: durable and frequent interactions, when coupled with low frictions, compound into a persistent advantage.

The next section concludes the study, summarizes scientific contributions and practical implications, and outlines directions for extending the product-analytics framework to wider datasets and time horizons.

6.3. Limitations and validity of the conclusions

First, the market coverage is restricted to Binance Spot/USDT. Cross-exchange heterogeneity and derivatives markets are not incorporated; therefore, absolute levels of TI/PDA are exchange-specific rather than market-wide benchmarks. Second, ECP and $ILLIQ$ are proxy variables. RCP differs from the Level-1 best-quote spread and reflects intraday extremes. The daily Amihud measure for mega-cap assets often approaches zero, reducing its interpretability. Nonetheless, in relative, cross-asset comparisons these indicators preserve decision-relevant information and remain fit for comparative inference. Third, TI captures transaction intensity rather than (DAU/MAU). In the absence of complete on-chain, entity-level attribution, TI should be interpreted as an approximate layer of product usage rather than a census of unique users. Finally, the observation window – January-July 2025 – fixes a specific market regime. Extrapolation to other phases of the cycle requires re-estimation using the same procedures and robustness checks to validate stability across regimes.

These limitations do not invalidate the practical significance of the results. On their basis, product positioning was articulated and targeted improvements of key performance indicators were proposed to strengthen the competitive standing of the analyzed cryptocurrencies.

6.4. Practical implications for positioning

From a product perspective, competitiveness is governed by two critical axes: 1) reduction of transactional frictions and 2) expansion of sustained interaction. Operationally, improvement requires lowering the cost of use by tightening price ranges and fees, stabilizing liquidity flow (SV), and stimulating repeated micro-interactions (higher TI/PDA). For assets such as BNB, the principal reserve lies in engineering growth of interactions without eroding the existing friction advantage. For DOGE, priorities are the reduction of ECP and risk; otherwise, moderate activity will not translate into persistent product usage. For BTC/ETH, maintaining depth and the stability of the flow is sufficient to preserve their lead in PCI. The Product Competitiveness Index offers a transparent assessment of cryptocurrency positioning. It captures user-activity persistence, interaction intensity, and frictional constraints through product-proxy metrics. The results show substantial cross-asset differences in behavioral and product characteristics; incorporating these features enables more accurate ranking than reliance on traditional market indicators alone. Accordingly, the findings support the effectiveness of the proposed product-oriented framework and the integral index as a practical tool for evaluating cryptocurrency competitiveness.

These results support broader conclusions on behavioral metrics in product analytics. They highlight key factors shaping asset competitiveness and emerging market trends.

The following subsection considers the advantages and disadvantages of the proposed methodology.

6.5. Advantages and disadvantages of the methodology

The advantage of the proposed methodology is its scalability through the addition of new metrics. In addition, the weighting system allows it to be personalized according to user needs. This will be reflected at the stage of experiment design.

The disadvantage of the proposed methodology is the need to collect and accumulate statistical data on assets. However, this disadvantage is insignificant if powerful information technology is used.

The following subsection will consider the practical application of the proposed methodology.

6.6. Practical application of the methodology

The practical significance of the methodology lies in its ability to establish a foundation for new standards in product analytics. These standards apply specifically to the field of digital assets. The proposed model can be used for:

– strategic positioning of crypto projects based on behavioral indicators;

– monitoring the dynamics of user engagement and network effects;

– evaluating the effectiveness of marketing and communication campaigns in the context of real product and user value.

Based on the above, it is possible to formulate generalized conclusions.

Conclusion

This study develops a methodology for assessing the competitiveness of cryptocurrencies, in which each asset is considered as a digital product with measurable parameters of behavior, transactions, and user experience. The PCI was formalized using min–max normalization and linear convolution with predefined weights, integrating six standardized indicators: product-driven activity, search volume, transaction intensity, illiquidity, conversion efficiency, and user retention.

It has been empirically demonstrated that behavioral and product-level metrics provide higher discriminative power than market-based indicators for ranking cryptocurrency competitiveness. The obtained PCI ensures cross-asset comparability, robustness to weighting changes, and independence from price levels. The results confirm that friction, liquidity, and

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persistence jointly determine product competitiveness, establishing a reproducible framework for behavioral evaluation of digital assets.

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