Journal of Social Research

P-ISSN: 2827-9832
E-ISSN: 2828-335x
http://ijsr.internationaljournallabs.com/index.php/ijsr

Factors Influencing Millennials and Generation Z's Trust in Crypto-Based Payments in Indonesia

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ABSTRACT

Cryptocurrency adoption in Indonesia is rising, yet trust barriers persist, particularly among Millennials and Gen Z. Despite growing transaction volumes (IDR 475.13 trillion by 2024), gaps remain in understanding trust drivers specific to this demographic. This study investigates factors influencing trust in crypto-based payments, testing hypotheses on privacy, anonymity, traceability, expectations, and satisfaction. A quantitative cross-sectional design surveyed 195 Indonesian respondents (purposive sampling) using PLS-SEM analysis in SmartPLS 4.0, assessing measurement and structural models, predictive relevance, and IPMA. Trust significantly boosts adoption intention (t = 20.279, p = 0.000), driven by expectations (t = 5.898) and satisfaction (t = 2.096), while privacy, anonymity, and traceability showed no significant impact. IPMA revealed trust as high-importance but low-performance, urging strategic improvements. Results guide policymakers and businesses to prioritize transparency, user experience, and education over privacy-centric features. Future research should expand demographics, integrate qualitative methods, and compare crypto with other payment systems (e.g., CBDCs).

Keywords: Cryptocurrency adoption; Payment Option; Millennials and Gen Z; User intention to use; Indonesia

INTRODUCTION

The development of information and communication technology has brought major changes in the payment system in Indonesia. This transformation is characterized by the increasing use of digital technology, the expansion of internet access, and the increasing adoption of electronic devices (Hallikainen & Laukkanen, 2018; Herskind et al., 2020; Hong & Thong, 2013; Indonesia, 2018). One form of payment system innovation that is growing is electronic money, including digital wallets and prepaid cards. Over time, cryptocurrencies or cryptocurrencies have emerged as new alternatives, utilizing blockchain technology that offers security, transparency, and decentralization of transactions (Hsiao et al., 2015; *International Organization for Standardization (ISO 9000:2015)*, n.d.; *ISO/IEC 27001:2013 – Information Technology – Security Techniques – Information Security Management Systems – Requirements*, n.d.; Joinson et al., 2010; Mendoza-Tello et al., 2018).

Bitcoin has been a pioneer in the use of crypto since its introduction in 2008, and since then various other crypto assets have started to emerge, both as a medium of exchange and investment instruments (Fröhlich et al., 2020; Gao & Waechter, 2017; Garaus & Treiblmaier, 2021; Hair et al., 2019, 2021). In Indonesia, although crypto has not been recognized as an official tender in accordance with Bank Indonesia regulations, its trading activities have been regulated by BAPPEBTI since 2019 as a digital commodity. Based on BAPPEBTI data, the value of crypto transactions in Indonesia reached IDR 475.13 trillion until October 2024, with 75% of its users coming from the age of 18-35 years, namely the Millennial generation and generation Z.

As part of the initial study, researchers distributed a short questionnaire to 39 respondents from Millennials and Gen Z to understand their views on the use of cryptocurrencies as a means of transaction. The results of this questionnaire show some interesting findings (Firmansyah & Dede, 2022; Folkinshteyn & Lennon, 2016; Fortes et al., 2017), 60% of respondents stated that they are willing to use crypto for future transactions of goods or services (Bhatia, 2018; Conti et al., 2018; Ermakova et al., 2017). This shows that there is an initial enthusiasm for crypto as an alternative to payments, although there are still 40% who are not sure. Regarding the level of understanding, most respondents were at a moderate level, 41% answered a scale of 3, and only 5.1% felt very familiar (scale 5). This indicates that there is still a large room for public education regarding the basic concepts of cryptocurrencies (Bernabe et al., 2019; Casino et al., 2019).

Regarding trust, 43.6% of respondents believe crypto is a secure payment method, although only 7.7% strongly trust (Beals et al., 2015). There are still about 28.2% who are skeptical and 20.5% who choose neutral, indicating that security is still a major concern. In terms of the factors that most affect trust in crypto, the most answers point to transaction security (28.2%), followed by transaction media/platforms (30.8%), as well as other factors such as regulation and price fluctuations (Abramova & Böhme, 2016; Alalwan et al., 2021; Albayati, 2022; Al-Debei et al., 2013; Alharbi & Sohaib, 2021). However, when asked if crypto will replace conventional payment methods, most are still hesitant. 61.6% of respondents chose a scale of 2–3, indicating that they see the potential of crypto, but are not yet fully convinced of a complete transition in the near future. Simply put, despite the fact that quite a lot of people have shown interest, only 7.7% of respondents have ever actually used crypto for payments. This confirms the existence of a gap between intent and practice, likely due to barriers such as access, education, or trust of the system.

This study advances prior research (Abramova & Böhme, 2016; Alshamsi & Andras, 2019) by specifically examining trust formation in crypto-based payments among Millennials and Gen Z in Indonesia, a demographic underrepresented in existing literature. While prior studies (Folkinshteyn & Lennon, 2016; Shahzad et al., 2018) focused on general adoption drivers, this research uniquely dissects the non-significance of privacy, anonymity, and traceability—contrary to common assumptions—and highlights user expectations and satisfaction as primary trust determinants (Almarashdeh et al., 2018; Alsalami & Zhang, 2019; Alshamsi & Andras, 2019; Arias-Oliva et al., 2019; Badawi & Jourdan, 2020). Additionally, it employs PLS-SEM with IPMA (Hair et al., 2021) to prioritize actionable strategies for enhancing adoption, a methodological refinement over earlier works (Sohaib et al., 2019). The study also addresses Indonesia's regulatory context (BAPPEBTI, 2019), offering localized insights absent in global surveys (Treiblmaier et al., 2021).

METHOD

This study employs a quantitative approach with a cross-sectional design, collecting data at a single point to analyze relationships between variables. It includes hypothesis testing and correlation analysis to examine the strength of these relationships without inferring causality. Data was gathered via questionnaires based on the research model, targeting specified subjects.

The study uses purposive sampling, selecting respondents from Indonesia's Millennial and Gen Z generations who have or have not used crypto for transactions. The sample size was determined using Hair's formula (number of indicators multiplied by six), resulting in a minimum requirement of 186 respondents due to 31 indicators. Following Hair's guideline of 100–200 samples for studies with over 20 indicators, the researchers collected responses from 195 participants to reduce potential errors.

The distribution of respondents by domicile and occupation is illustrated in Figures 2 and 3, respectively.

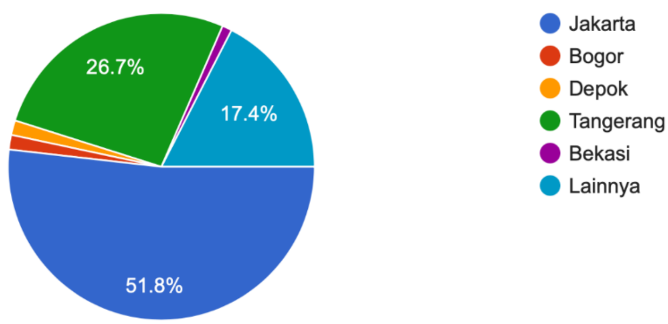

Figure 1. Distribution of Respondent Data by Domicile

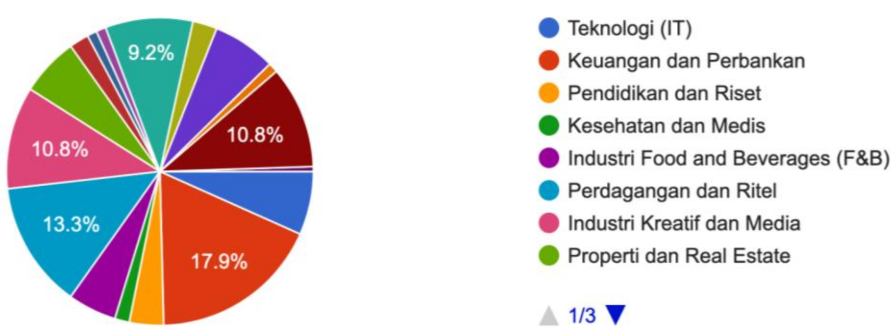

Figure 2. Distribution of Respondent Data by Occupation

Primary data was collected via a closed-ended Google Form questionnaire using a 1–5 Likert scale ("Strongly Disagree" to "Strongly Agree"). The structured questionnaire ensured data alignment with research needs without open-ended responses.

The study employed multivariate analysis using PLS-SEM, suitable for examining complex relationships without requiring normal distribution or large samples. Analysis was conducted in SmartPLS 4.0, evaluating:

- Outer Model: Assessed reliability and validity through outer loading (≥0.7), Cronbach's Alpha, composite reliability (≥0.7), AVE (≥0.5), and HTMT discriminant validity (≤0.85).
- Inner Model: Examined construct relationships via VIF (<3), R^2 (0.25=weak, 0.5=moderate, 0.75=strong), and effect size f^2 (0.02=small, 0.15=medium, 0.35=large).
- Predictability: Tested using Q^2 and CVPAT (comparing PLS-SEM RMSE with other models).
- Hypothesis Testing: Bootstrapping assessed significance (t-stat > 1.645, $p < 0.05$, 95% CI excluding zero).
- IPMA: Evaluated variable importance and performance for managerial insights and future research.

RESULTS AND DISCUSSION

Based on the data displayed from the questionnaire distributed, all respondents came from the Millennial and Z generations, with the majority aged 25-34 years old (71.3%). This shows that most of the respondents are in productive age and have experience in transactions, both conventionally and digitally. Female respondents (52.3%) are slightly more than men (47.7%), indicating that interest in crypto is not limited by gender.

Most respondents work in the Finance and Banking sectors (17.9%), but still reflect diverse backgrounds. As many as 83.1% are full-time workers and 73.8% have at least a Diploma or Bachelor's education, followed by Postgraduate (15.4%), which indicates that the level of literacy and understanding of respondents is quite high in answering questionnaires.

In terms of behavior, the majority of respondents have never made transactions using cryptocurrencies (87.2%) and the intensity of their use is still very low (84.6%). This indicates that while the current adoption rate is minimal, there is potential for future crypto growth, depending on various factors that affect their interest.

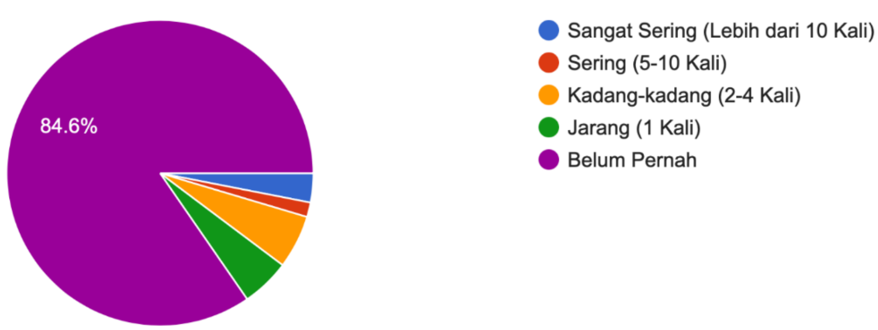

Figure 3. Frequency Rate of Payments Using Cryptocurrencies
Source: processed from questionnaire

Measurement Model

Before testing the relationships between constructs in the structural model (inner model), an important first step in the PLS-SEM approach is to test the measurement model. The main goal of this test is to ensure that each latent construct is accurately measured by the indicators that represent it. Thus, the measurement model test aims to assess the reliability and validity of the research instrument, including internal reliability tests, convergent validity, and discriminant validity. In this study, all constructs were developed as reflective models, so the test was carried out by paying attention to the outer loading values, Cronbach's Alpha, Composite Reliability, Average Variance Extracted (AVE), and Heterotrait-Monotrait Ratio (HTMT) to ensure the quality of the model measurement before entering the stage of analyzing the relationship between constructs in the structural model.

Based on the results of the outer model analysis on SmartPLS, all indicators in this study have an outer loading value above 0.70, indicating that the indicators are valid in representing their respective constructs (Hair et al., 2021). In addition, the results of the reliability test through Cronbach's Alpha and Composite Reliability also showed values above 0.70, which indicates that the constructs used have excellent internal consistency.

The validity of the convergence was also strengthened by the value of the Average Variance Extracted (AVE) on all constructs exceeding the minimum limit of 0.50, which means that the indicators are able to explain the variability of the construct well. On the other hand, the discriminant validity test using HTMT also showed that all values between constructs were below the threshold of 0.85, so it can be concluded that each construct has an empirically clear differentiation.

The test results are in Appendix 1, Appendix 2, and Appendix 3.

Structural Model

Collinearity Test

The collinearity test is performed to ensure the absence of multicollinearity between exogenous constructs. In this study, the Variance Inflation Factor (VIF) value of all indicators was below the maximum limit of 5, even most of them were below 3. This shows that there is no high correlation between the predictor variables, so the constructed tested is feasible for use in structural models. Thus, no indication of violation of the collinearity assumption was found in the model.
The results are found in Appendix 4.

Significance Test

The significance test was carried out by observing *t-statistical* and *p-value* values in the relationship path between latent variables. The results of the test showed that two significant relationships were: *Perceived Expectation* to *Perceived Trust* (t = 5,898, p = 0.000) and *Perceived Trust* to *Intention to Use* (t = 20,279, p = 0.000).

Meanwhile, other relationships such as *Perceived Anonymity*, *Perceived Information Privacy Risk*, *Perceived Satisfaction*, and *Perceived Traceability* to *Perceived Trust* have a p-value

of > 0.05, so they are not significant. This shows that only expectations and trust play a real role in explaining user intentions.
The results are found in Appendix 5.

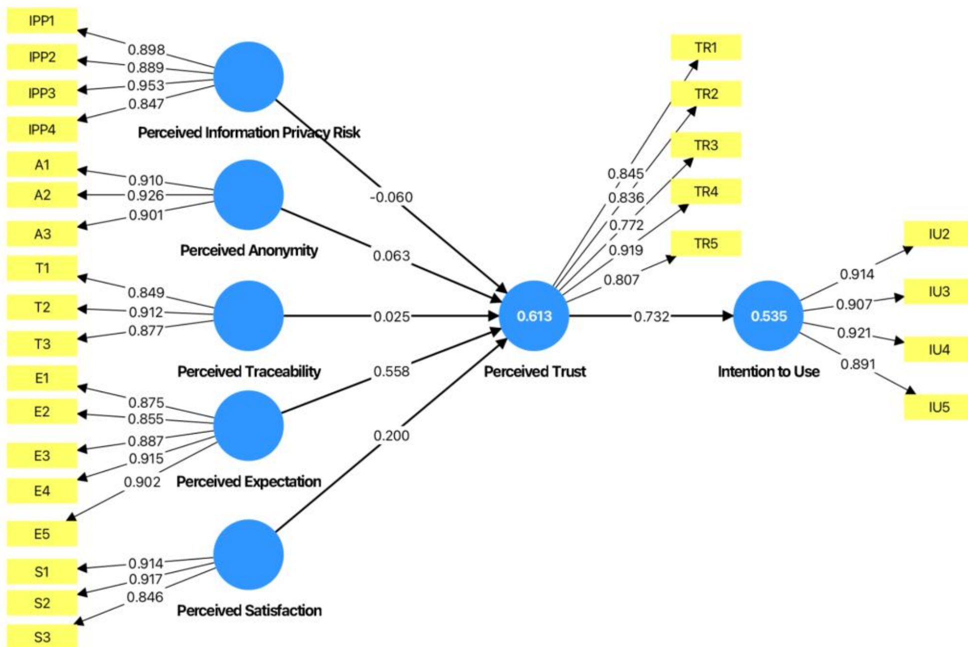

Figure 4. Research Model Results
Source: processed by researchers with Smart PLS

Uji Predictive Relevance

The predictive ability of the model was evaluated through *the Q² Predictive Relevance* and *the Cross-Validated Predictive Ability Test* (CVPAT). The Q^2 values for the *Perceived Trust* and *Intention to Use* constructs are both more than 0, which indicates that the model has predictive relevance.
In CVPAT, *the PLS loss* value for *Intention to Use* (0.719) and *Perceived Trust* (0.847) was lower than *the IA loss* (1.211 and 1.413), as well as *the mean loss difference* was negative and significant ($p < 0.001$). This proves that the model has better predictive capabilities than the baseline model.

Uji Explanatory Power

The R-square value indicates how much the variability of endogenous constructs can be explained by exogenous constructs. The R^2 for *Perceived Trust* is 0.613 (strong category), while the R^2 for *Intention to Use* is 0.535 (moderate category). This means that about 61.3% of the variation in trust and 53.5% of the variation in crypto usage intent can be explained by the constructs in the model.

Based on the results of hypothesis testing in this study, it is known that not all independent variables have a significant influence on *the Perceived Trust* mediation variable. The first hypothesis (H1) that Perceived *Trust* has a positive influence on *Intention to Use* was accepted, with a *t-statistic* value of 20,279 and *a p-value* of 0.000, showing a very significant relationship.

This indicates that the higher the respondents' trust in the crypto system, the higher their intention to use it as a means of payment.

Meanwhile, the second hypothesis (H2) which states that *Perceived Information Privacy Risk* has a positive effect on *Perceived Trust* is rejected, because the *t-statistic* value is only 1.249 and the *p-value* is 0.212. This means that concerns over privacy risks are not strong enough to increase user trust in this context. The same thing also happened to the third (H3) and fourth (H4) hypotheses, namely *Perceived Anonymity* and *Perceived Traceability Against Perceived Trust*, which had *p-values* of 0.336 and 0.697, respectively. These two hypotheses were also rejected because they did not show a significant influence.

On the other hand, the fifth hypothesis (H5) regarding the influence *of Perceived Expectation* on *Perceived Trust* was declared accepted, with a *t-statistic* value of 5.898 and *a p-value* of 0.000. This shows that users' expectations of the crypto system play an important role in shaping their trust. Likewise, the sixth hypothesis (H6), namely *Perceived Satisfaction* with *Perceived Trust*, which has a *t-statistic* value of 2.096 and *a p-value* of 0.036, which is also accepted.

In conclusion, the H1, H5, and H6 hypotheses were accepted, while H2, H3, and H4 were rejected because they were not statistically significant (p-value > 0.05). This suggests that trust in crypto is formed primarily by user expectations and satisfaction, while privacy, anonymity, and traceability aspects have not had a significant influence on forming trust.

Impact Performance Map Analysis (IPMA)

Based on the results of the Importance-Performance Map Analysis (IPMA), a visualization was obtained that divided the research indicators into four quadrants based on the level of *importance* (total influence on "Intention to Use") and *performance* (level of performance/perceptual performance based on respondents' assessments). This analysis is important to identify strategic priority areas in encouraging the use of cryptocurrencies as a means of payment, especially among Millennials and Gen Z in Indonesia.

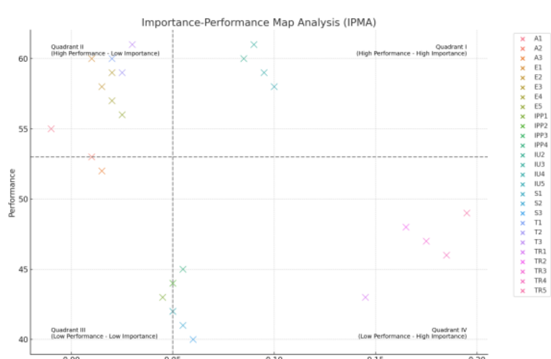

Figure 5. IPMA from Construct Intention to Use
Source: processed by researchers with Smart PLS

In Quadrant I (High Importance – High Performance), the indicators in this position show that they not only have a great influence on intention to use, but have also been rated well by respondents. Indicators of *the Intention to Use* construct such as IU2, IU3, IU4, and IU5 are included in this quadrant. This means that strategies related to these factors are already effective, and need to be maintained to maintain the positive momentum of crypto technology adoption in daily transactions.

Meanwhile, Quadrant II (Low Importance – High Performance) contains indicators that are considered to have high performance, but the level of influence on the intention of use is relatively low. While not the main focus in driving crypto adoption, these indicators are still important because they can support the overall user experience and reinforce a positive perception of the system. This high performance needs to be maintained to support a stable adoption ecosystem (Nurhalizah et al., 2024; Patil et al., 2020; Rehman et al., 2019).

Quadrant III (Low Importance – Low Performance) includes indicators that currently do not have a significant influence on the intention of use and are also considered to be poor in performance. Indicators in this quadrant, such as some items from the *Perceived Information Privacy Risk* or *Perceived Anonymity* constructs, have not yet become a top priority for strategic interventions. However, this does not mean that it should be completely ignored. If there is a shift in focus or user needs in the future, these indicators can receive further attention (Lovelock & Wirtz, 2011; Luhmann, 1979; Manimuthu et al., 2019; Martin, 2018; Mashatan et al., 2022).

The most crucial are the indicators in Quadrant IV (High Importance – Low Performance). Indicators from *the Perceived Trust* construct such as TR1 to TR5 occupy this position, indicating that they have a huge impact on the intention to use cryptocurrencies, but they still perform poorly in respondents' perceptions (Nainggolan et al., 2023; Nur Hasanah & Mediasari, 2024). This is a signal for decision-makers to immediately make improvements or strengthen aspects that form trust, such as transaction security, transparency, platform integrity, and regulatory support. Interventions in this quadrant have the potential to result in a significant increase in crypto adoption intentions in the future (Kim et al., 2015; Klinger & Svensson, 2018; Krombholz et al., 2016; Longo et al., 2020).

Overall, IPMA provides practical guidance for policymakers and crypto payment system developers. Focusing on improving performance on high-importance but low-performing indicators will have a significant impact on accelerating crypto adoption in Indonesia.

Discussion

Based on the results of all tests in this study, it can be concluded that the research model built through the PLS-SEM approach is generally of good quality and able to explain the relationship between constructs empirically. The measurement model test shows that all indicators meet the requirements for validity and reliability. This is reflected in the outer loading value which is all above 0.7, the composite reliability value which exceeds 0.7, and the Average Variance Extracted (AVE) value is above 0.5, as suggested by Hair et al. (2021). Discriminant validity is also achieved because the entire HTMT value is below the 0.85 threshold, which means that each construct is unique and does not overlap with the other constructs.

Furthermore, the results of the internal model test show that the R-square value for *Perceived Trust* is 0.613 and for *Intention to Use* is 0.535. This value indicates that the model has good explanatory capabilities—with exogenous constructs being able to explain more than 60% of variability in *Perceived Trust* and more than 50% in *Intention to Use*. The effect size (f^2) test showed that only the *Perceived Expectation* construct had a moderate effect on *the Perceived Trust*, while the others had a small or insignificant effect. The results of testing the significance of the relationship between constructs through bootstrapping tests reinforce these findings, with only three statistically significant hypotheses (H1, H5, and H6), namely the effect *of Perceived Trust* on *Intention to Use*, *Perceived Expectation* on *Perceived Trust*, and *Perceived Satisfaction* on *Perceived Trust*. Meanwhile, the other three hypotheses were rejected because the p-value was greater than 0.05.

The collinearity test also shows that there is no problem of multicollinearity because all VIF values are below 3, so each independent construct makes a unique contribution to the model. The predictive ability of the model is also confirmed through Q-square values and CVPAT analysis, where the Q^2 value for the endogenous construct is greater than 0 and the loss value in the PLS model is smaller than the baseline model (IA loss), which means that the model has good predictive ability on observational data.

The results of the IPMA analysis also provide a practical view, where the indicators of the *Perceived Trust* construct (TR1–TR5) have a high level of influence on the intention of use, but still underperform. These findings show that the trust aspect is the main key in encouraging crypto adoption by the younger generation, but it needs to be improved in terms of public perception. These indicators should be the focus of the development of communication strategies, system security, and public education by crypto service providers and policymakers.

Overall, the model is able to provide a comprehensive picture of the factors that influence the intention to use crypto as a payment method, and confirms that *Perceived Trust* plays an important role that must be built through user expectations and satisfaction. These findings are expected to be a scientific and practical contribution in supporting the digital transformation of finance in Indonesia.

CONCLUSION

This study found that while trust in the crypto system significantly boosts adoption intention, privacy, anonymity, and traceability had no notable impact, highlighting the need for improved transparency, security, and user experience to drive acceptance. Future research should expand variables (e.g., digital literacy, trust in government), include broader demographics (e.g., Gen X, diverse regions), and employ mixed-methods approaches for deeper insights. Additionally, comparative studies with other payment systems (e-wallets, CBDCs), longitudinal tracking of adoption trends, and investigations into behavioral and regulatory influences could yield richer, more actionable findings. Addressing these gaps would enhance strategies for businesses and policymakers in fostering crypto adoption.

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