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Research article

Evaluating the acceptance of CBDCs: experimental research with artificial intelligence (AI) generated synthetic response

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Abstract: This research examines the factors that influence the public's expectation for more information, acceptance or rejection of central bank digital currencies (CBDC). Using generative AI (ChatGPT 4.0), responses were simulated to mimic CBDC adoption scenarios, considering demographic attributes, such as gender, income, education, age, level of financial literacy, network effect, media influence, and merchant acceptance. A total of 663 synthetic responses were generated and analyzed using statistical methods and multinomial logistic regression to assess the probability of acceptance, rejection, or waiting for more information to decide. The chi-squared automatic interaction detection (CHAID) model showed a high performance in correctly classifying cases of acceptance, indecision, and rejection, presenting an accuracy of 92.6%. Multinomial logistic regression revealed that factors, such as educational level, financial experience, and income level, significantly influence the decision to accept a CBDC. This method also shows a high performance, as it obtained an accuracy of 96.4%. These results are in line with previous research and underline the effectiveness of generative AI as a reproducible and low-cost tool for analyzing hypothetical scenarios. Generative AI, with its algorithmic fidelity, has great potential for predicting human behavior in economic contexts. However, synthetic data may not capture the complexities and nuances of actual human decision making. As a result, certain contextual factors, emotional influences, and unique personal experiences that may significantly influence an individual's decision to accept or reject CBDC may be overlooked.

Keywords: CBDC adoption; Large Language Models; AI Generative; survey experiment; synthetic responses; behavioral finance; digital finance

JEL Codes: B26, C53, G40, G41

Abbreviations: AI: Artificial Intelligence; CBDC: Central Bank Digital Currency; CHAID: Chi-squared Automatic Interaction Detection; Df: Degrees of Freedom; Exp (b): Exponentials of b; LLMs: Large Language Models; TAM: Technology Acceptance Model; TPB Theory of Planned Behavior; TRA: Theory of Reasoned Action.

1. Introduction

Central bank digital currencies (CBDCs) represent a significant innovation in the global financial system (Lekhi et al., 2024). CBDCs are the digital equivalent of fiat money and are issued by central banks. These digital currencies issued by central banks offer an alternative to cash and cryptocurrencies. They leverage blockchain technology to facilitate fast, secure, and transparent transactions. In a context where the digitization of finance is unstoppable, CBDCs emerge as a key government response to modernize payment and settlement systems, as well as to address challenges, such as financial inclusion (Náñez Alonso et al., 2020a; Náñez Alonso et al., 2021a; Ngo et al., 2023). However, their implementation poses regulatory, technical, and privacy challenges that need to be carefully addressed (Samudrala and Yerchuru, 2021).

The importance of CBDCs lies in their potential to revolutionize the financial system in several ways. First, they enable instant transactions (Sethaput and Innet, 2023) and a reduction in transaction costs (Ahiabenu, 2022; Náñez Alonso et al., 2020a). Second, they improve the traceability and security of payments (Dunbar, 2023). Third, CBDCs can help to mitigate illicit activities by providing greater control and transparency in financial transactions (Dunbar, 2023; Oh and Zhang, 2022; Wang, 2023). Fourth, they can help to improve the sustainability of the financial system by being less energy-intensive than other digital payment methods (Náñez Alonso et al., 2021b; Alonso, 2023; Ozili, 2023a).

According to the 2022 Bank for International Settlements (BIS) report, 93% of central banks around the world have indicated that they were doing some type of work linked to a CBDC (Kosse and Mattei, 2023). Many central banks have made public announcements that reveal their intention to research, develop, and issue a CBDC in the distant future, such as the Bank of England and Central Bank of Brazil. The common motivations for issuing a CBDC are the need to modernize payment systems, the demand for more secure and efficient solutions, and the opportunity to improve financial inclusion by providing access to banking services to underserved populations (Das et al., 2023; Ozili, 2023a; Ozili and Alonso, 2024). Regarding financial inclusion, some central banks, especially those in developing countries, have considered using CBDC to broaden financial inclusion by offering zero-cost or low-cost CBDC accounts that have fewer onboarding documentation requirements and offline capabilities so that the unbanked population can easily own a CBDC account and use it to access basic financial services without needing internet connectivity which may be expensive for low-income and poor unbanked adults (Ozili, 2022). This ensures greater access to basic financial services for unbanked adults living in remote locations where there is no formal banking infrastructure and where there is no internet connectivity.

However, the known challenges of issuing a CBDC are the risk of financial disintermediation (Wenker, 2022), concerns about privacy, cybersecurity, and potential disruption and stability in traditional financial systems (Das et al., 2023; Náñez Alonso et al., 2020a; Tercero-Lucas, 2023; Tronnier et al., 2022). Despite these challenges, central banks continue to make progress in researching, developing, and issuing CBDC. Currently, only four countries have implemented a CBDC: the Bahamas with Sand Dollar (Wenker, 2022), Jamaica with JAM-DEX (de Sèze, 2023), the six countries that comprise the Eastern Caribbean Central Bank (Antigua and Barbuda, Grenada, St. Kitts and Nevis, Dominica, St. Lucia, St. Vincent and the Grenadines; and two British Overseas Territories: Anguilla and Montserrat) with D-Cash (Náñez Alonso et al., 2023), and Nigeria with e-Naira (Ozili, 2024). Only one country, El Salvador (Alonso et al., 2024), has adopted a digital currency (i.e., Bitcoin) as legal tender, in coexistence with the money issued by its central bank. Further, significant CBDC developments have also been observed in Asia-Pacific region. For instance, China's CBDC, the digital yuan or the e-CNY, is transforming payments in the region (Lee et al, 2021), and its success is mostly attributed to strong government push and effective collaboration with banks and digital financial services providers (Wang, 2023; Mu, 2023; Shen and Hou, 2021). India has also rolled out a CBDC, the digital Rupee, to broaden access to financial services for the Indian population (Di Maggio et al, 2024). In contrast, Pacific Island countries have not yet adopted CBDC, but they are rapidly developing digital money capabilities in preparation for CBDC issuance even though its successful adoption will likely depend on the resilience of Pacific Island countries' monetary and financial conditions, digital infrastructure, institutional (legal, regulatory, and supervisory) frameworks, and the maturity of domestic payment systems (Zhou et al, 2024; ABD, 2023).

Despite the growing interest in CBDCs by central banks, it is often argued that the success of CBDC depends to a large extent on its acceptance by the population (Bijlsma et al., 2024). Therefore, countries, currency areas, and jurisdictions that are considering issuing a CBDC need to understand the factors that drive and hinder CBDC acceptance in order to design effective policies and strategies (Lee et al, 2021). The adoption of a CBDC involves not only technological implementation, but also the public's trust and willingness to use it in their daily lives (Bijlsma et al., 2024; Tronnier et al., 2022; Zarifis and Cheng, 2023). Therefore, it is essential to explore both the drivers and barriers that influence the acceptance of a CBDC.

The scarcity of empirical data on user behavior towards CBDCs makes research in this field particularly challenging. The reason is that, as has been pointed out, since there are so few countries or currency areas that have implemented CBDC in a real environment, there is limited availability of real-world data on its use and acceptance. In this context, experimentation with generative artificial intelligence (AI) offers a promising avenue to simulate and analyze potential scenarios of acceptance or rejection of CBDC. This can provide valuable insights into how citizens might interact with CBDC and what factors are critical for its acceptance.

Recent work suggests that language models, such as GPT, can make human-like judgments across a number of domains (Dillion et al., 2023). Park et al. (2024) conducted a test with 1,052 real people, applying large linguistic models to qualitative interviews about their lives and then measuring the extent to which these agents reproduce the attitudes and behaviors of the people they represent and obtained an accuracy of 85%. In this study, we have used generative AI tools to model and experiment with different variables that may influence the acceptance of a CBDC. For this purpose, and after conducting a literature review on the individual factors that may affect the acceptance or rejection of a CBDC, the following individual factors were identified: age, gender, educational level, income level, knowledge about the financial system, influence of their environment (family or friends), and the sources of information that the subject consults (social networks, television, newspapers, etc.). We generated a prompt that was sent to Open AI's ChatGPT 4.0 generative AI. In it, we described the scenario of a country with inhabitants that have different socioeconomic characteristics. Once this was done, we asked whether they would accept CBDC, reject it (and therefore opt for cash or other means), or wait for more information before making a final decision. A total of 663 synthetic responses were generated. The responses obtained through the simulation are consistent with other empirical data. Large language models (LLMs) could allow researchers to pilot studies via simulation first, searching for novel social science insights to test in the real world (Horton, 2023). Therefore, our study is novel and represents a breakthrough in the field of digital finance as it offers an effective, easily replicable, and low-cost method to analyze hypothetical acceptance or rejection scenarios using simulated data (Kazinnik, 2023; Korinek, 2023). Generative AI, therefore, has great potential to determine human behavior in economic analysis contexts (Dillion et al., 2023; Horton, 2023; Filippas et al., 2024). The results obtained will allow policy makers and financiers to better understand the underlying dynamics and to design more informed and effective strategies for the issuance and adoption of CBDCs. However, the use of LLMs as simulated economic agents has raised questions about the extent to which these models can realistically represent human behavior in the financial domain. On the one hand, these models offer an unprecedented ability to simulate complex economic environments (Dillion et al., 2023; Horton, 2023; Filippas et al., 2024; Xie et al., 2024). They are scalable, adaptive, and can process huge volumes of data without the cognitive biases of humans (Gu et al., 2024; Kamath et al., 2024). Moreover, by reducing the need for costly experiments, they allow for faster and more efficient hypothesis testing (Kazinnik, 2023; Korinek, 2023). However, their limitations are obvious. Although they can mimic decision-making patterns, they lack true economic rationality and human intuition. Their behavior is strictly tied to the data on which they were trained, which can lead to biased or unrealistic results (Dai et al., 2024; Echterhoff et al., 2024; Kamath et al., 2024). Moreover, validating their simulations remains a challenge, as they do not learn and evolve autonomously as a human agent would.

Our study contributes to literature in several ways. Our study contributes to the financial innovation literature that examines the factors that encourage or hinder the acceptance of new financial innovations. Our study adds to the financial innovation literature by using a unique AI-driven simulation method to generate insights into the factors that encourage or hinder the acceptance of a financial innovation by the population in a simulation environment, with particular focus on CBDC. The study also contributes to the CBDC literature that examines the factors affecting the adoption of CBDC. The study also contributes to on-going policy debates about the role of AI in the transformation of digital money. Our study shows that AI simulation methodologies can offer insights to central banks on the factors that encourage CBDC acceptance by the population. Central banks can use such insights to understand whether its CBDC will be accepted before issuing the CBDC in the real world. The rest of the study is structured as follows. Section 2 presents a review of literature on the determinants of CBDC acceptance. Section 3 describes the methodology. Section 4 reports the results. Section 5 discusses the results. Section 6 concludes the study.

2. Literature review

Citizens will accept and use technological innovations if they perceive that they have advantages and are easy to use. The technology acceptance model (TAM) is crucial to understanding the adoption of new technologies, as it predicts that people will use an innovation if they perceive it as useful and easy to use. This model is based on the theories of reasoned action (TRA) and planned behavior (TPB), which emphasize the influence of attitudes and perceptions on behavior. TAM stresses the importance of usability and perceived usefulness in the acceptance and effective use of innovative technologies. These models have previously been used in the field of digital finance by Alonso et al. (2023), in their study on the gender gap in the acceptance and use of cryptocurrencies; Or in the study by Liu et al. (2022) and Erwanti and Prasetyani (2023) on the possible acceptance of Chinese CBDC (eCNY) and Indonesian CBDC respectively. Also, Tronnier and Kakkar (2021) and Tronnier et al. (2023) used this same method in their study to validate the intention to use the future digital euro. This method is based on a series of determining factors that must be analyzed in order to determine the influence or not on the acceptance of technology, including gender, age, income level, and education.

In the context of CBDC, it is crucial to consider possible gender differences to ensure an inclusive and effective implementation. The adoption of CBDC requires not only advanced technology, but also the public's trust and willingness to use it in their daily lives. Therefore, understanding gender variations in the perception and adoption of CBDCs can help design policies that encourage greater acceptance among all groups in society. Thus, research by Kanwal et al. (2021) and Alonso et al. (2023) indicates that men and women show different behaviors in the adoption of new technologies, including CBDCs. Men tend to value perceived usefulness more and have more favorable attitudes towards the use of digital technologies, while women tend to focus more on ease of use and security. Ozili (2023b) indicates that men are more likely to adopt electronic payments and digital technologies, while women show more concerns about privacy and security. Bijlsma et al. (2024) in their study on CBDCs and their acceptance in Europe report an important fact: men have nine percentage points more intention to open an account (with CBDCs) than women. Fujiki (2023) examined the variables that influence the acceptance and use of a CBDC in Japan and found that gender is a variable to be considered when it comes to CBDC implementation. The same conclusion is also reached by Ozili (2022) in his study on the factors affecting the acceptance of e-Naira CBDC in Nigeria, as well as Liu et al. (2022) for the case of China. Therefore, gender is an important factor to be considered when assessing the possible acceptance or rejection of a CBDC in any country or currency area. This is due to the fact that differences in behavior between men and women with respect to CBDCs are observed in the academic literature analyzed.

Another factor to consider when analyzing the implementation of CBDC is the income level of the citizens of the country or currency area in question. First, Tan (2023) shows that countries with higher levels of income inequality face more challenges in adopting CBDC. People with lower incomes tend to have less access to digital infrastructure and less trust in formal financial institutions, which may limit their willingness to adopt CBDC (Tan, 2023). The relationship between income level and CBDC uptake has been the subject of several studies. Zhou et al. (2024) show that Pacific Island countries, such as Micronesia, Papua New Guinea, and Solomon Islands, have the highest poverty rates and wide income inequality which hinders the adoption of digital money including CBDC. This indicates that the income level of citizens in Pacific Island countries may affect the acceptance of CBDC. Mohammed et al. (2023) show that income inequality has a significant impact on CBDC adoption, and countries with high income inequality tend to face more challenges in implementing these technologies, possibly due to lower accessibility and trust in the formal financial system by lower income segments. Ngo et al. (2023) use deep learning techniques with information obtained from Facebook and found that income level (income inequality) has a direct effect influence on citizens' perception of CBDCs. The study by Xia et al. (2023) also found a direct relationship between income level and acceptance of a CBDC in their study with data from China. The findings of Xia et al. (2023) indicate that lower-income segments have less trust and limited access to digital infrastructure. In contrast, we find that the study by Bijlsma et al. (2024) indicates that the intention to adopt CBDC is unrelated to income level.

The International Monetary Fund states in one of its reports that citizens' level of education is a key variable to consider when analyzing and assessing whether citizens will accept the use of CBDC (Tan, 2023). In turn, there are several studies conducted in different countries that include the level of education as a determining factor. Thus, we can point to the study by Ogunmola and Das (2024) on India, the study conducted on Indonesia by Erwanti and Prasetyani (2023), the study conducted by Sun (2023) on East Asian countries, Liu et al. (2022) for the case of China, Ozili (2023a) for the case of African nations, Ozili and Alonso (2024) for the case of the four jurisdictions that have already launched their CBDC (Bahamas, Jamaica, Eastern Caribbean Central and Nigeria), and the case of Canada in Huynh et al. (2020). In contrast, we find the study of Bijlsma et al. (2024) which states the intention to adopt CBDC is also not related to the level of education. From this we can conclude that perhaps in less developed countries with a lower level of education, education is a fundamental variable in determining whether CBDC is accepted. While in more developed countries with a higher level of education it may be a less influential factor. However, for the most part we see that the level of education is a determining factor to be considered when determining whether a CBDC will be accepted by the inhabitants of a country or currency area that intends to issue a CBDC.

Kiff et al. (2020) in a study by the International Monetary Fund and Huynh et al. (2020) of the Bank of Canada explored the idea that central banks recognize the age factor as an obstacle to the digitization of the monetary system. And the fact is that the adoption of new financial technologies, such as CBDCs, generally varies with age (Náñez Alonso et al., 2020b; Koziuk, 2021; Mohammed et al., 2023). Young people tend to be more receptive to the adoption of new digital technologies due to their greater familiarity and comfort with electronic devices and digital platforms (Koziuk, 2021). However, Alfar et al. (2023) indicates that demographic groups with high levels of financial exclusion, such as rural populations and younger age groups, may have difficulty in adopting new CBDC due to difficulties in accessing new technologies. Therefore, age can be a favorable or unfavorable factor when it comes to accepting the use of a CBDC depending on whether we are dealing with countries or currency areas with developed or developing economies (Náñez Alonso et al., 2021a). The study by Bijlsma et al. (2024) also shows that age is a determining factor, since it shows that, depending on age, if the CBDC equaled or exceeded the benefits of the cards, the CBDC showed greater acceptance. The study by Bijlsma et al. (2024) also shows young people under 35 years of age are more likely to adopt CBDC. Náñez Alonso et al. (2020b) also find the highest percentage of CBDC acceptance in people between 18 and 25 years of age. Bijlsma et al. (2024) find that CBDC use decreases with age. This same conclusion is reached by other studies, such as that of Dunbar and Treku (2024) and Fernández-Villaverde et al. (2020), when they indicate that the intention to use and the amount of money that would be deposited in a savings account with CBDC varies with age. People aged 35 years or older tend to deposit less money in a CBDC account compared to people aged 34 years or younger. On the other hand, we find some studies, such as Kasemrat and Kraiwanit (2022), in Thailand indicating that age does not seem to be a determining factor in accepting the use of a CBDC. Therefore, age is mostly found to be a factor to be considered when testing the possible acceptance or rejection of a CBDC.

Financial culture and previous experience in the world of finance can play a role in the acceptance of CBDCs. Thus, the study conducted by Amarta and Latifah (2023) in Indonesia, among individuals from millennials and Z generations, found that both financial culture and digital readiness significantly affect the willingness to use CBDCs. Meanwhile, the study by Niroula (2024) found that individuals with a higher level of financial literacy have higher adoption of CBDCs. Gupta et al. (2023) conducted a randomized controlled trial where they found that individuals with a higher level of financial literacy tend to be more receptive. Specifically, after receiving information about CBDC, an increase in the acceptance of CBDC was achieved in the treatment group versus the control group. Participants with high financial literacy showed greater increases in perceived credibility and adoption of CBDC after the informational intervention (Gupta et al., 2023).

CBDC adoption will depend not only on user demand but also on merchant acceptance, which directly impacts its practical utility (León et al., 2024; Mohammed et al., 2025). If widely accepted by merchants, users will have stronger incentives to adopt it (Bank for International Settlements (BIS), 2021). Therefore, merchant adoption is a key factor shaping the success of CBDCs (Schumacher, 2024). Despite the possible introduction of CBDC and its acceptance as a means of payment at merchants, Maino and Pani (2024) indicate that various means of payment will most likely continue to coexist, such as cash and card payments.

Along with the above factors, another one emerges that should not be overlooked: the network effect. That is, that users' decisions are interdependent. In order to study this effect, previous studies have resorted to the agent-based model, including León et al. (2023) and Wang and Gao (2023). Authors such as Fernández-Villaverde et al. (2020) have previously studied the impact that the network effect can have on the acceptance of a CBDC. Knowledge about CBDCs and the importance people place on privacy also influences adoption intention. People who know what CBDC is, are more likely to adopt a current account with CBDC, with this effect being more pronounced among younger people. Trust in the central bank and in banks in general does not have a significant effect, but trust in the bank itself and in other people does (Fernández-Villaverde et al., 2020). The possible network effect has also been studied by Niroula (2024) in an experimental study. Niroula (2024) finds that after informational intervention, CBDC acceptance increased by 3.75% in the treatment group compared to the control group. Also, Wang and Gao (2023) examine how this network effect can be increased. They recommend that the network effect can be increased by using CBDC for government payments, such as fines and salaries, ensuring a convenient user experience and promoting peer-to-peer (P2P) payments. These measures aim to increase the adoption of CBDC among both consumers and merchants. Also, there are authors, such as Abraham (2021), who argue that cryptocurrencies can exert influence on CBDC acceptance or rejection through the network effect.

The effect that news in the media has on public opinion has been widely demonstrated in various studies such as those of Kepplinger (2008) and Robinson (2016). In the study by Wang (2022), it is stated that media coverage in the modern era has a diverse and multidimensional impact on the public. Despite the diversity of platforms, the influence of media in daily life continues to increase. However, alongside traditional media, social networks have also emerged as "shapers of public opinion". Anjaria and Guddeti (2014) show in their study the power that the social network Twitter has on public opinion. Also, the social network Instagram can play a fundamental role in shaping public opinion, especially through the so-called "influencers" according to the study by Casaló et al. (2020). In short, these social networks such as Twitter (now X), Instagram or Youtube itself stand as means to shape public opinion on some issues; especially among the young population (Lozano-Blasco et al., 2023). There are three recent examples of how the opinion of relevant people through social networks can influence people's behavior in relation to digital currencies. The first case has to do with the Tweets published by Elon Musk about the adoption of cryptocurrencies by his companies, and the "explosion in price" it caused which is shown in the study of Shahzad et al. (2022). The second is related to the publication of information on social networks that called into question the solvency of Terra (stablecoin), which finally led to its collapse (Ferretti and Furini, 2023; Fernández et al., 2024). The third one relates to the crisis of several American banks such as Silicon Valley Bank (SVB) and how massive withdrawals of funds from SVB occurred due to the panic generated on social media networks (Lyócsa et al., 2023). Therefore, the media, both traditional (television, newspaper) and social networks can play a very important role in influencing the adoption or rejection of a CBDC.

Regarding the use of generative AI to generate responses to a survey through models, such as ChatGPT, Perplexity, or Bard (to name a few), there are already studies that validate its use and defend it. For instance, Argyle et al. (2023) conclude in their research that language models, such as GPT-3, can serve as effective surrogates for specific human subpopulations in social science research. Despite known problematic biases, the algorithmic bias of GPT-3 is detailed and demographically correlated, allowing it, with appropriate conditioning, to accurately emulate the response distributions of diverse human groups. This property, termed algorithmic fidelity, suggests that language models with this capability can be powerful tools for advancing understanding of humans and society (Amirova et al., 2024; Argyle et al., 2023). Also, in the field of psychology, studies by Dillion et al. (2023) and Grossman et al. (2023) conclude that the use of LLMs, such as GPTs achieve great results when investigating the response distributions of diverse human groups using synthetic surveys. Lee et al.'s (2023) study on global warming concludes that LLMs, such as GPT-4, can effectively emulate human behaviors and perceptions, demonstrating algorithmic fidelity.

In the field of economics, we find two studies that have previously validated the use of generative AI as a surrogate for human populations to conduct research. First, Kazinnik (2023) concludes that the use of LLMs to generate synthetic survey responses to bank run scenarios can simulate diverse populations with specific demographic characteristics. Moreover, the simulated responses and their results align with previous empirical studies. Second, the consumer behavior study conducted by Brand et al. (2023) concludes that LLMs, such as GPT-3.5, can be effective tools for understanding consumer preferences. By generating hundreds of survey responses, GPT-3.5 showed behaviors consistent with economic theory and the marketing domain. Third, Horton (2023) points out that LLMs, due to their training and design, act as implicit computational models of humans, referred to as *homo silicus*. They can be endowed with resources, information, and preferences to explore their behavior in simulations. Experiments based on this approach show qualitatively similar results to classical studies, allowing researchers to pilot studies and seek new insights in social science before testing them in the real world.

3. Materials and methods

3.1. Materials

In order to validate the use of generative AI to simulate and analyze potential scenarios of acceptance or rejection of a CBDC, a prompt has been created that describes a scenario for the general public with varied demographic attributes such as gender, income, education, and age. It presents the influence of social networks and friends on financial decisions. Given the news of the launch of a

CBDC, the media disseminates messages about CBDC. The prompt asks whether, with this information and considering social and media influences, the person would decide to withdraw his/her money from the bank or accept the CBDC. The prompt can be found in the additional material section. With this, 663 synthetic responses have been generated as if a real person were responding to the questions and the situation described. The responses are collected in a dataset included in the supplementary material section. For robust quantitative studies, a sample of between 300 and 500 participants is recommended, as this range of responses allows for meaningful statistical analysis and reduces the margin of error; however, for larger research or research involving multiple variables, samples of between 500 and 1000 responses are appropriate to capture the diversity of the market. To ensure the statistical validity of our study, we selected a sample size of 663 responses, based on the formula for calculating large samples or infinite populations. Since we took large populations as reference, such as the United States of America (+/−335 million inhabitants) and Europe (+/−741 million inhabitants), working with a confidence level of 99% ($z=2.576$) and a margin of error of 5% ($e=0.05$), assuming a distribution of maximum variability ($p=0.5$). A sample of 663 responses meets the statistical requirements for valid inference in large populations. Based on scientific literature, we can argue that a sample of more than 500 responses such as ours is perfectly valid, as previous studies on CBDC have been validated with 494 responses in the case of Lamberty et al. (2024), 638 in the case of Wu et al. (2024), and with 400 responses in the case of Soukal et al. (2024).

3.2. Methodology

Following other authors, such as Argyle et al. (2023), Lee et al. (2023), and Kazinnik (2023), and through the literature review, the main variables that can influence the decision to accept, reject, or wait for more information to decide on a CBDC have been detected. Once this has been done, we proceeded to write a prompt with a text that asks the question about acceptance or rejection of the CBDC. In the wording of the prompt (which is available as additional material at the end of the manuscript) all the variables identified during the literature review that may influence an individual’s decision have been included: gender, income, education, age, network effect, identity statement, media, and acceptance by merchant. In the case of the gender variable, the responses generated by the model reflect a binary classification, assigning individuals to the category of male or female. For the income variable, the model structures its responses within five predefined ranges: less than 25,000 euros, between 25,000 and 50,000 euros, between 50,000 and 75,000 euros, between 75,000 and 120,000 euros, and more than 120,000 euros.

In terms of educational level, the responses are organized into six categories: no high school, high school, university, postgraduate, master’s, and doctorate. Regarding age, the model categorizes individuals into five groups: 18–24 years old, 25–34 years old, 35–54 years old, 55–64 years old, and over 65 years old.

In the case of the network effect, the model incorporates scenarios in which an individual is influenced by different opinions in his or her environment. In one situation, a friend expresses his rejection of CBDCs, while another emphasizes their benefits and decides to accept them. On the other hand, in the identity variable, the model assigns individuals one of three predefined profiles: person with no financial knowledge, someone with experience in finance, or a cryptocurrency enthusiast. Regarding the media variable, the model’s responses reflect three main sources of information: social networks such as Twitter, newspapers and television news. Finally, with respect to merchant acceptance, the responses generated follow a dichotomous structure, indicating that CBDCs can be widely accepted and easy to use, or on the contrary, have low acceptance and be impractical for merchants.

With this, we wrote the following prompt where we asked ChatGPT 4.0 to pretend to be a citizen: Given this information, do you plan to reject, wait for more information, or accept the CBDC? In addition, we asked ChatGPT 4.0 to include an explanation or rationale for the decision. In this way, AI itself makes the decision and justifies the reason for its decision. Just as if it were a human being. The prompt has been executed in ChatGPT 4.0 to generate synthetic responses. Thus, the number of answers indicated in the materials section is generated. The dataset is available in the supplementary material section. Figure 1 shows the methodology used.

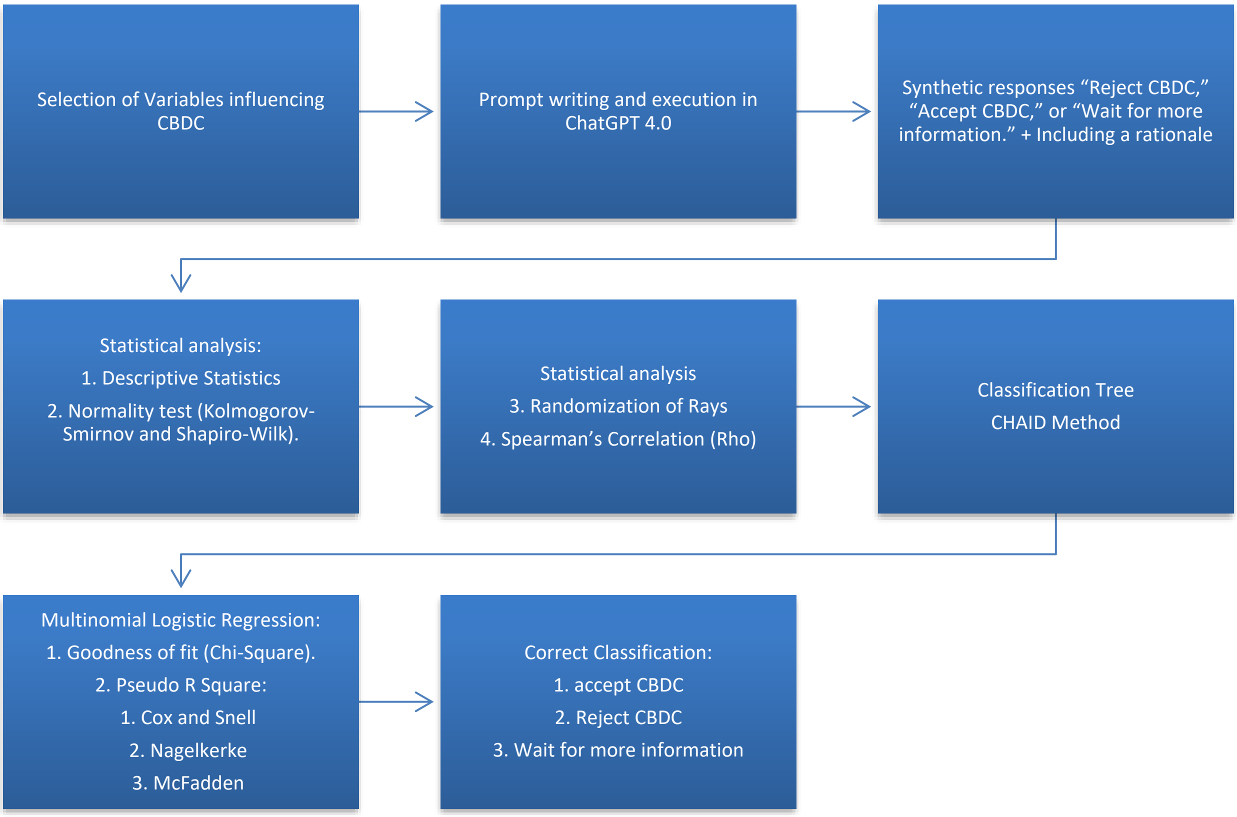

Figure 1. Applied methodology. Source: Own elaboration.

The responses were then processed statistically. The first thing that has been done is the descriptive statistics of the data, in which both basic statistical measures and frequency tables have been prepared to see how the different variables are distributed as in previous studies such as those of Batrancea et al. (2020), Ioan et al. (2020), Alonso (2023), and Mohammed et al. (2024). Second, the normality assumptions of these variables have been checked through the Kolmogorov-Smirnov and Shapiro-Wilk tests following previous studies such as Gupta et al. (2023) and Masciandaro et al. (2018). Third, randomization has been executed from the gust test, with the aim of knowing what type of tests more in line with the data are available, as well as to characterize the variables themselves, following previous studies, such as Choi et al. (2022) and Niroula (2024). Fourth, we proceeded to perform the correlations between variables using Spearman’s rho coefficient, since these are not quantitative variables but categorical variables, as in previous studies, such as those of Jun and Yeo (2021), Náñez

Alonso et al. (2021a), and Náñez Alonso et al. (2024). Fifth, we have classified the available data according to the final decision they make through the classification tree following the CHAID method, discriminating by the variables that are statistically related to the classification variable, a method used in studies such as Carbo-Valverde et al. (2020).

The CHAID model is represented by a conditional segmentation function (Equation 1):

$$Y = f(X_1, X_2, \dots, X_n) \quad (1)$$

where f is a class assignment function defined by the CHAID tree. Each tree splitting is based on the following condition:

$\chi 2(X_i, Y) > \alpha$

where:

- $\chi 2(X_i, Y)$ is the chi-square statistic between the explanatory variable X_i and the target variable Y (in our case wait for more info, accept CBDC, or reject CBDC).
- α is the statistical significance threshold.
- X_1, X_2..., X_n are the predictor variables, which in our case are gender, income, education, age, level of financial literacy, network effect, media influence, and merchant acceptance.

Finally, we proceeded to perform a multinomial logistic regression, attempting, as in the classification tree, a classification according to the decision taken to profile the sample, a method followed in previous studies, such as Fujiki (2021), Li (2023), Fujiki (2023), and Mohammed et al. (2024).

If the dependent variable Y has K categories (in our case wait for more info, accept CBDC, or reject CBDC), then we choose a base category and model the probability of each remaining category in relation to it. The equation for each k category (k=1..., K-1) is expressed as (Equation 2):

$$\log\big(P(Y=0)/P(Y=k)\big) = \beta_{k0} + \beta_{k1}X_1 + \beta_{k2}X_2 + \cdots + \beta_{kn}X_n \quad (2)$$

where:

- P(Y=k) is the probability that the observation belongs to category k,
- P(Y=0) is the probability of the base category,
- βk_0, βk_1, ..., βk_n are the estimated coefficients for category k,
- X_1, X_2, ..., X_n are the predictor variables, which in our case are gender, income, education, age, level of financial literacy, network effect, media influence, and merchant acceptance.

To obtain the probability of each category, we use the SoftMax function (Equation 3):

$$P(Y=k) = \frac{e^{\beta_{k0}+\beta_{k1}X_1+\cdots+\beta_{kn}X_n}}{1+\sum_{j=1}^{K-1} e^{\beta_{j0}+\beta_{j1}X_1+\cdots+\beta_{jn}X_n}} \quad (3)$$

And the probability of the base category is calculated (Equation 4):

$$P(Y=0) = \frac{1}{1+\sum_{j=1}^{K-1} e^{\beta_{j0}+\beta_{j1}X_1+\cdots+\beta_{jn}X_n}} \quad (4)$$

To validate the result, we have checked here both the goodness of fit (chi-square), as well as the pseudo r-square through Cox and Snell, Nagelkerke, and McFadden tests.

All this, to check if a correct classification is made in the decision made by the subject about whether to accept the CBDC, wait for information, or withdraw the money. And thus, determine that this method is valid in studies on acceptance and use of a CBDC.

4. Results

Table A.1 in the appendix presents the descriptive statistics of the sample. The distribution of the data reflects a relatively balanced sample in terms of gender, with a slight predominance of the value 0 in the gender variable and a standard deviation of 0.5. The variables related to perception and acceptance, such as network effect, identity statement, media, and merchant acceptance, show mean values close to 0.50 or 2, indicating moderate perceptions and behaviors in these aspects. The decision variable shows a mean of 1.33, with a median of 1, suggesting a tendency towards lower values on the scale. In terms of skewness, a relatively symmetrical distribution is observed in most of the variables, although with slight tendencies towards negative values in variables, such as network effect (−0.015) and mean (−0.119). In contrast, decision shows a positive skewness of 1.397, suggesting a higher concentration of low values and a distribution with a longer right tail. Regarding kurtosis, most variables show negative values, indicating flatter (platykurtic) distributions compared to normal. The negative values in gender (−2.001), network effect (−2.006), and Mean (−1.530) stand out. However, the decision variable is the only one with a positive kurtosis (1.000), suggesting a more pointed distribution and concentrated around the mean.

Table 1 presents the results of two normality tests: Kolmogorov-Smirnov and Shapiro-Wilk, applied to gender, income, education, age, network effect, identity statement, media, merchant acceptance, and decision. Both tests assess whether the data follows normal distribution. As observed, for all variables, both the Kolmogorov-Smirnov and Shapiro-Wilk tests yield significance values (Sig.) of 0.000, which is below the standard threshold of 0.05. This indicates that the null hypothesis of normality is rejected for all cases. Consequently, none of the variables in the dataset follow a normal distribution.

Table 1. Normality tests.

	Kolmogorov-Smirnov[a]		Shapiro-Wilk	
	Statistician	Sig.	Statistician	Sig.
Gender	0.350	0.000	0.636	0.000
Income	0.169	0.000	0.893	0.000
Education	0.138	0.000	0.906	0.000
Age	0.161	0.000	0.887	0.000
Network effect	0.343	0.000	0.637	0.000
Identity statement	0.218	0.000	0.800	0.000
Media	0.247	0.000	0.786	0.000
Merchant acceptance	0.342	0.000	0.637	0.000
Decision	0.434	0.000	0.613	0.000

Note: a indicate Lilliefors significance correction. Source: Own elaboration.

Table 2 presents the results of the runs test for the same variables. This test evaluates the randomness of a sequence of data by analyzing whether values above and below a cutoff point (i.e., the median) follow a random pattern. The results indicate that most variables do not significantly deviate from randomness, as their asymptotic Sig. are all above the standard threshold of 0.05. This suggests that the distributions of income, education, age, identity statement, and media follow a random pattern. The network effect variable, while exhibiting a relatively high Z-score (1.440), still does not reach statistical significance (Sig. = 0.150), indicating a tendency toward randomness but not conclusively. On the other hand, the variables gender, merchant acceptance, and decision present extreme cases as they have only one gust, meaning that all values are concentrated on one side of the cutoff point. This lack of variation strongly suggests non-randomness in these variables.

Table 2. Gust test.

	Gender	Income	Education	Age	Network effect	Identity statement	Media	Merchant acceptance	Decision
Test value[a]	0[b]	3	3	3	1	2	2	0[b]	1[b]
Cases < Test value	0	270	221	264	329	205	207	0	0
Cases ≥ Test value	663	393	442	399	334	458	456	663	663
Total cases	663	663	663	663	663	663	663	663	663
Number of gusts	1[c]	327	292	312	351	298	290	1[c]	1[c]
Z		0.476	−0.321	−0.548	1.440	1.253	0.385		
Sig. asin. (bilateral)		0.634	0.748	0.584	0.150	0.210	0.700		

Note: a. Median, b. All values are greater than or less than the cutoff. The streak test cannot be performed. c. Only one gust occurs. The gust test cannot be performed. Source: Own elaboration.

4.1. Result of the Spearman's Rho correlation

Figure 2 and Table A.2 in the appendix show Spearman's correlation analysis (Rho).

The strongest correlation observed in the table is between network effect and decision, with a high positive correlation (r = 0.64). This finding suggests that the influence of a person's social network significantly impacts their decision-making, reinforcing the idea that social connections shape individual choices. Another notably strong correlation is between identity statement and decision (r = −0.32), indicating that personal identity perceptions have a negative but meaningful impact on decisions, which may reflect differing perspectives or attitudes associated with self-identification. A moderate negative correlation is observed between media and age (r = −0.084), suggesting that older individuals may be less influenced by media. Likewise, there is a weak negative correlation between gender and network effect (r = −0.048), implying that gender differences have a minor influence on how individuals perceive or engage with network effects. Regarding the weakest correlations, the relationship between gender and Decision (r = −0.003) shows an almost negligible association, indicating that gender does not play a significant role in decision-making. Similarly, the correlation between income and media (r = −0.034) is very low, suggesting that income level does not strongly relate to perceptions of media influence. Finally, the correlation between merchant acceptance and decision (r = −0.015) is minimal, implying that merchant acceptance does not have a direct impact on individual decisions in this sample.

Figure 2. Spearman's Rho correlation analysis. Source: Own elaboration based on SPSS and Python V. 3.12.

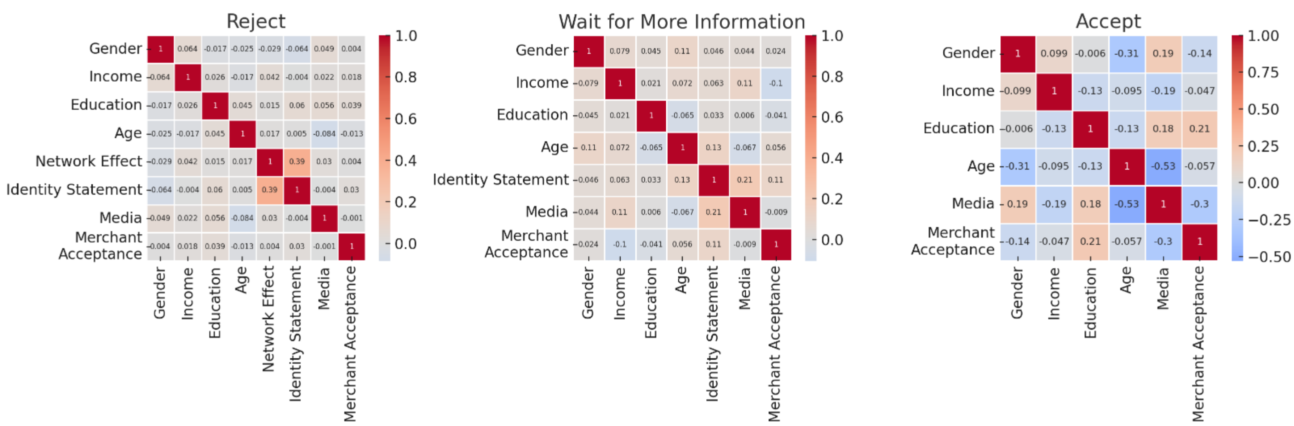

Figure 3. Spearman's Rho correlation segmented by decision withdraw money, wait for more information or accept CBDC. Source: Own elaboration based on SPSS and Python V. 3.12.

As shown in Figure 3, the correlation patterns vary across the three decision categories: reject, wait for more information, and accept. In the reject category, a weak negative correlation is observed between network effect and identity statement, indicating that people with stronger identity statements might be less influenced by social networks when rejecting an option. For the wait for more information category, the strongest correlation statistically occurs between the variable's identity declaration and media directly, suggesting that those who identify themselves as more crypto enthusiasts also use digital media, such as Twitter, to inform about financial issues. In the accept category, media and age are the variables that stand out for their moderately negative correlation, suggesting that those accepted by younger people are informed through digital media, such as Twitter.

4.2. Results derived from the classification tree following the CHAID method

Figure 4 and Table 3 show the results derived from the classification tree following the CHAID method.

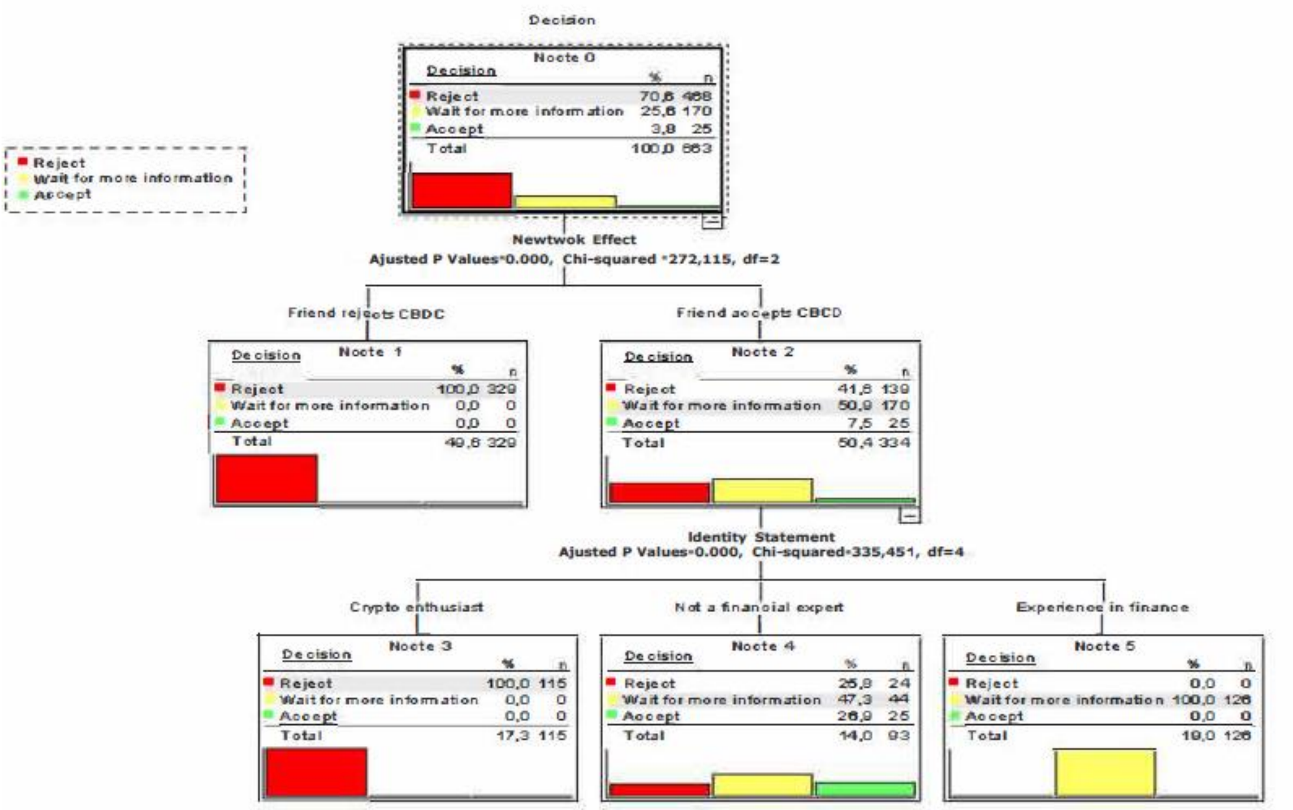

Figure 4. Classification tree. Source: Own elaboration based on SPSS.

Table 3. Classification tree results.

Observed	Predicted			
	Reject	Wait for more information	Accept CBDC	Correct percentage
Reject	444	24	0	94.9%
Wait for more information	0	170	0	100.0%
Accept CBDC	0	25	0	0.0%
Global percentage	67.0%	33.0%	0.0%	92.6%

Source: Own elaboration based on SPSS.

Figure 4 and Table 3 illustrate the classification tree results for the three possible decisions: reject, wait for more information, and accept CBDC. The CHAID method was used to predict decision outcomes based on key discriminating variables, including network effect and identity statement. The classification tree shows that the network effect is the main variable that influences decision making. People whose friends reject the CBDC are more likely to do the same, while those who have friends who accept the CBDC are more inclined to wait for more information or accept it. Among those whose friends accept the CBDC, the identity statement further differentiates decisions. Those with financial experience and people without financial experience are more likely to expect more information, while those who are crypto enthusiasts are more inclined to turn them down. Overall, by using identity statement and network effect, the model achieves high classification accuracy. The best-ranked category is rejection, with 94.9% correctly classified. The wait for more information category is perfectly ranked (100.0%), while accept CBDC does not show correct predictions. The overall accuracy of the classification is 92.6%.

4.3. Results of the logistic regression

Tables 4 and 5 show the results of a logistic regression, including goodness-of-fit measures and pseudo-R-squares, respectively, which allow us to assess the model's ability to explain the variability in the data.

Table 4. Goodness of fit.

	Chi-squared	Df	Sig.
Pearson	140.580	1256	1.000
Deviation	109.608	1256	1.000

Source: Own elaboration.

Table 5. Pseudo R-square.

Cox and Snell	0.720
Nagelkerke	0.944
McFadden	0.885

Degrees of Freedom (Df) Source: Own elaboration.

The goodness-of-fit statistics indicate that the model adequately represents the data. Pearson's chi-square value (140.580, df = 1256, p = 1.000) and the deviance value (109.608, df = 1256, p = 1.000) suggest that there is no significant discrepancy between the observed and expected values, implying that the model fits the data well. The high p-values indicate that the model does not significantly deviate from the observed distribution. Regarding the pseudo-R squares, the model demonstrates a strong explanatory power. Cox and Snell's pseudo-R square is 0.720, indicating that the model accounts for 72% of the variance in the dependent variable. Nagelkerke's pseudo-R square, which adjusts Cox and Snell's measure for better interpretability, is even higher at 0.944, suggesting that the model explains 94.4% of the variance. McFadden's pseudo-R square, which is typically more conservative, is 0.885, further confirming a strong model fit.

These results indicate that the logistic regression model is highly effective in explaining the variability in the dependent variable. The Pearson and deviance chi-square tests suggest a well-fitting model, while the pseudo-R square values provide strong evidence that the model explains a substantial proportion of the total variance. This high explanatory power supports its reliability for predicting and analyzing the factors influencing the dependent variable.

Table A.3 in the appendix presents the parameter estimates for the three decision categories: rejecting CBDC, waiting for more information, and accepting CBDC. A multinomial logistic regression was conducted using all available variables, with CBDC acceptance as the reference category. This approach helps determine how various factors influence the likelihood of withdrawing money or waiting for more information instead of accepting CBDCs. Table A.3 includes the exponentials of b (Exp[B]), representing odds ratios that indicate how strongly each variable is associated with the decision outcome. An Exp(B) greater than 1 suggests that an increase in the independent variable raises the likelihood of the corresponding decision, whereas an Exp(B) below 1 implies a decreased probability.

For the first model (rejecting CBDC versus accepting it), gender does not significantly impact the decision (Exp[B] = 0.719, p = 0.637). Income levels also show no substantial influence, with extremely small Exp(B) values, indicating negligible predictive power. However, network effect has an Exp(B) of 1.63E9, suggesting a strong positive influence on the decision to reject CBDCs. Similarly, identity statement plays a significant role, with individuals identifying as crypto enthusiasts or financially inexperienced being far more likely to reject CBDCs.

In the second model (waiting for more information versus accepting CBDC), individuals aged 18–25 show a slightly higher probability of waiting for more information (Exp[B] = 9.60, p = 0.090), although this is not statistically significant. Notably, identity statement strongly influences this decision, with Exp(B) values as high as 3.94E11, indicating that self-perceived financial identity substantially impacts the likelihood of waiting rather than accepting CBDCs. Media consumption also plays a role, with high Exp(B) values suggesting a notable influence of information sources on decision-making.

Overall, the logistic regression results indicate that network effects, identity statement, and media consumption are key factors in predicting rejection or hesitation regarding CBDC adoption. Gender and income, on the other hand, show limited significance in influencing these decisions.

Table 6 shows the results observed and predicted by the algorithm, as well as the percentages of correct classification for each decision category: reject, wait for more information and accept CBDC.

Table 6. Observed vs. predicted classification.

Observed	Predicted			
	Reject	Wait for more information	Accept CBDC	Correct percentage
Reject	457	1	10	97.6%
Wait for more information	3	163	4	95.9%
Accept CBDC	3	3	19	76.0%
Global percentage	69.8%	25.2%	5.0%	96.4%

Source: Own elaboration.

The final classification analysis shows that the algorithm correctly classifies 96.4% of cases using the available data. Specifically, the model achieves an accuracy of 97.6% for individuals who decide to reject CBDCs, correctly identifying 457 out of 468 cases. Additionally, it classifies 95.9% of those who decide to wait for more information, making it the second-best performing category. The classification accuracy for those who accept CBDCs is lower at 76.0%, correctly identifying 19 out of 25 cases. These results indicate that the algorithm performs exceptionally well in predicting rejection and hesitation (waiting for more information), with accuracy rates above 95%. However, its performance is slightly weaker in predicting acceptance, where it correctly classifies three out of every four cases. Despite this, the overall classification performance remains high, demonstrating the model's robustness in predicting decision-making behavior regarding CBDCs.

4.4. Results of the cross tabulated

Figure 5 presents the cross-tabulated results of the analysis. The heatmap for gender shows that both men and women predominantly choose to reject CBDCs, with similar distributions (242 women versus 226 men). The second most common choice is to wait for more information, while acceptance rates remain low for both genders (11 women versus 14 men). This suggests that gender does not play a significant role in determining acceptance, as both groups show a general reluctance toward CBDCs.

Regarding income, those earning between 25,000 and 50,000 euros show the highest tendency to wait for more information.

This suggests that individuals in this income bracket prefer a cautious approach before making a final decision. In contrast, the highest rejection rates are found among those earning less than 50,000 euros and those earning more than 120,000 euros, indicating that both lower- and upper-income groups are more skeptical about CBDCs. Notably, acceptance is lowest among the highest income group (>120,000 euros), where no individuals chose to accept CBDCs, reinforcing the idea that skepticism increases among wealthier individuals.

Individuals with no high school education or a Ph.D. are the most likely to reject CBDCs, while those with graduate or postgraduate education show a more balanced distribution between rejection and waiting for more information. Acceptance rates remain low across all education levels, with the highest percentage among Graduates holders, although still minimal.

This suggests that higher education does not necessarily translate into a greater willingness to adopt CBDCs but rather fosters a preference for additional information before deciding.

Younger individuals (25–34 years) show a strong inclination to wait for more information before deciding. This trend remains consistent across all age groups, with older people (65+) also showing high levels of hesitancy. Acceptance remains low across all age groups, with a slight increase among those 25–54 years old, although it is fairly balanced across all age groups.

The strongest influence of social networks is observed in rejection rates. Individuals whose friends reject CBDCs overwhelmingly follow the same choice (329 cases). In contrast, those whose friends accept CBDCs tend to wait for more information (170 cases), rather than immediately accepting them (25 cases). This highlights that positive perceptions about CBDCs do not necessarily lead to immediate adoption but rather encourage further investigation.

Individuals with no financial experience are the most likely to accept CBDCs, while cryptocurrency enthusiasts overwhelmingly prefer to withdraw their money (217 cases), with no cases of acceptance.

This pattern suggests a strong distrust of CBDCs among crypto enthusiasts, likely due to their preference for decentralized alternatives. On the other hand, those who lack financial experience prefer to wait for more information (44 cases), rather than rejecting CBDCs outright.

Regardless of the media source, the predominant decision is "reject", with the highest percentage among Twitter users (57 cases). Newspaper and TV news consumers exhibit similar hesitation levels, reinforcing a general trend of caution. Acceptance rates are lowest across all media sources, confirming a widespread reluctance to immediately adopt CBDCs. Merchant acceptance significantly influences CBDC decisions. When CBDCs are perceived as widely accepted (easy and convenient), individuals are more likely to wait for more information or accept them. However, when CBDCs are considered difficult and inconvenient, rejection rates are higher (237 cases). This suggests that the perceived usability of CBDCs plays a critical role in shaping adoption attitudes.

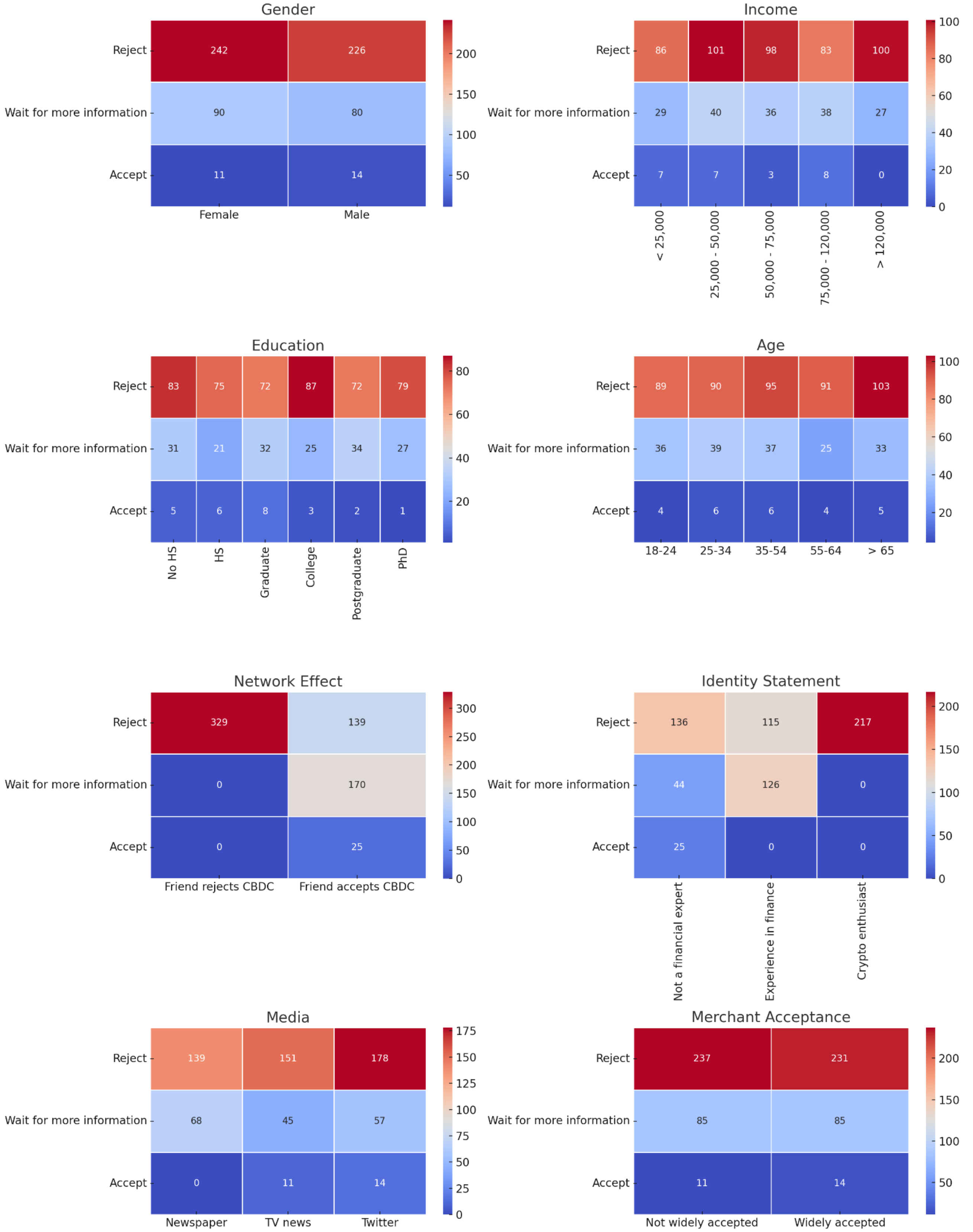

Figure 5. Results of cross tabulated decision. Source: Own elaboration based on Python V. 3.12.

5. Discussion

According to different authors in scientific literature, a sample size of at least 500 participants would be sufficient for robust case study research. For robust quantitative studies, a sample of between 300 and 500 participants is recommended, as this range of responses allows for meaningful statistical analysis and reduces the margin of error; however, for larger research or research involving multiple variables, samples of between 500 and 1000 responses are appropriate to capture the diversity of the market. Based on scientific literature, we can argue that a sample of more than 500 responses such as ours is perfectly valid, as previous studies on CBDC have been validated with 494 responses in the case of Lamberty et al. (2024), 638 in the case of Wu et al. (2024), and with 400 responses in the case of Soukal et al. (2024). Even with AI-generated synthetic responses, previous studies do not use very large samples. Park et al. (2024) conducted a test with 1,052 people and obtained an accuracy of 85%. Also, Liu et al. (2024) in their study on synthetic responses in the area of psychometrics use a dataset with 50 responses that then expand in the second phase to 100. In turn, Xiong et al. (2024) use 350 synthetic responses in their research.

The results from the Kolmogorov-Smirnov and Shapiro-Wilk normality tests indicate that none of the variables in the dataset follow a normal distribution, as all Sig. are below 0.05. This suggests that the dataset consists of heterogeneous observations, reflecting the diversity in individuals' characteristics and decision-making processes in real-world financial contexts. The correlation analysis reveals that most relationships between variables are weak, with only a few moderate correlations. The strongest positive correlation is observed between network effect and decision ($r = 0.64$), indicating that social influence plays a significant role in shaping individuals' choices regarding CBDC adoption. Conversely, identity statement and decision show a moderate negative correlation ($r = -0.32$), suggesting that self-perceived financial identity impacts decision-making, with financially confident individuals being more inclined to accept CBDCs. Other correlations, such as those between education and income, remain relatively weak, indicating that demographic variables have a limited direct effect on the decision. Interestingly, media and age present a slight negative correlation ($r = -0.084$), implying that older individuals might be less influenced by media in their decision-making process.

These findings suggest that while demographic factors have some influence, external social factors (network effect) and individual perceptions (identity statement) play a more prominent role in shaping attitudes toward CBDCs.

The decision classification tree results from the CHAID model indicate that network effect is the primary determinant of an individual's decision regarding CBDCs. The first split in the model occurs based on whether a person's friend accepts or rejects CBDCs. Individuals whose friends reject CBDCs overwhelmingly tend to do the same, while those whose friends accept CBDCs are more likely to wait for more information before deciding. Further segmentation reveals that identity statement plays a key role among those whose friends accept CBDCs. Individuals who consider themselves financially experienced show the highest likelihood of accepting CBDCs, while those identifying as crypto enthusiasts predominantly choose to reject CBDCs. Those without financial expertise tend to wait for more information rather than making an immediate decision. Regarding classification accuracy, the CHAID model correctly predicts 94.9% of cases where individuals reject CBDCs and 100% of those who choose to wait for more information. However, the model does not correctly classify any of the cases in which individuals accept CBDCs, suggesting that additional factors may influence acceptance. The overall classification accuracy of the model is 92.6%.

This non-parametric segmentation technique CHAID is an algorithm that generates readable assignment rules, with a direct and intuitive interpretation of the results. It also allows for the generation of more than two branches, which can lead to a more precise segmentation adapted to the data, as pointed out by Bertsimas and Dunn (2017). It also presents a series of limitations, such as requiring a large sample size to function optimally, in addition to the fact that all explanatory variables must be categorical or are converted into categorical ones, and it can be prone to overfitting if there are no adequate stopping criteria, as noted by Escobar Mercado (2002). However, it is also a statistical technique used in various investigations, such as those of Koyuncugil and Ozgulbas (2012), Delen et al. (2013), Jan (2018), Millán Solarte and Caicedo Cerezo (2018), Jan (2021), and Durica et al. (2023).

Turning to the logistic regression, the result from the goodness of fit and the pseudo R-square tests are quite insightful. We observe that the logistic regression model has a favorable goodness of fit score and a favorable pseudo R-square score from the Cox and Snell and Nagelkerke tests. This implies that the variables in the logistic regression model explain a large part of people's decision towards CBDC for both acceptance and rejection. The implication of our logistic regression model is that central banks and policymakers can rely on our model to assess people's decision to accept CBDC, reject CBDC, or to wait for more information before reaching a decision.

The multinomial logistic regression results indicate strong predictive performance. The model correctly classifies 96.4% of cases using the available data. Specifically, it achieves an accuracy of 97.6% in predicting individuals who reject CBDCs. Additionally, it correctly classifies 95.9% of those who choose to wait for more information, making it the most accurately predicted category. The classification accuracy for individuals who accept CBDCs is lower at 76.0%. Despite this, the overall classification accuracy remains high, demonstrating the model's robustness in predicting decision-making behavior regarding CBDCs. The results also shows that male individuals are more likely to accept CBDC than female individuals, and people who have high income not exceeding €120,000 are more likely to accept CBDC (or less likely to reject CBDCs). This result is relevant to policymakers and central banks. Central banks who intend to issue a CBDC should target more females so that the female population can accept and use CBDC as much as male individuals use CBDC. This result is consistent with the findings of previous studies such as Kanwal et al. (2021), Alonso et al. (2023), Bijlsma et al. (2024), and Fujiki (2023), showing that gender is a positive determinant of CBDC acceptance.

It was also found that highly educated people are more likely to accept CBDC than uneducated people. This result is relevant to policymakers and central banks. Central banks who have the intention to issue a CBDC should target educated people when distributing CBDC across the population. This is similar to the results of previous studies, such as Sun (2023), Liu et al. (2022), and Ozili and Alonso (2024), which show that education is a positive determinant of CBDC acceptance.

In the second model which evaluates the decision to wait for more information versus accepting CBDCs, we find that middle-aged and mature individuals are more likely to choose to wait for more information about CBDC before reaching a decision to accept or reject CBDC, compared to old individuals exceeding 65 years old. This result is also relevant to policymakers and central banks. Central banks who intend to issue a CBDC can choose to provide abundant information about CBDCs to mid-aged people to increase their likelihood of accepting CBDC when it is issued and distributed among the population. This result agrees with other previous studies such as those of Huynh et al. (2020), Náñez Alonso et al. (2020b), Koziuk (2021), and Mohammed et al. (2023), which show that age is a positive determinant of CBDC acceptance.

We also found that individuals who self-report that they (i) lack experience in finance, (ii) earn more €120,000, and (iii) are between 18 and 25 years old are more likely to choose to wait for more information about CBDC before reaching a decision. Meanwhile, those who self-report that they use TV news as a means of communication and information are able to reach a decision more quickly. This result is similar to previous research, such as that of Tan (2023), Mohammed et al. (2023), Ngo et al. (2023), Amarta and Latifah (2023), Niroula (2024), and Gupta et al. (2023), which show that age, experience in finance, and income are factors that people consider when making a CBDC decision. Policymakers and central banks are expected to consider these factors when rolling out CBDC.

Finally, the response obtained from the classification analysis of the response data using the AI algorithm shows that the predictive algorithm predicts that women are more likely to wait for more information than men, men are more likely to accept CBDC than women, people with middle-level income from €25,000 and €50,000 euros will prefer to wait for more information compared to low income and high income people, and people with non-formal education are likely to wait for more information than educated men. Young-aged individuals are more likely to wait for more information before deciding to accept or reject CBDC compared to older individuals. Also, the cross-tabulation classification analysis shows that graduated people, people with no experience in finance and people with network effect through recommendation from friends will more readily accept CBDCs. However, it is found that cryptocurrency enthusiasts, those who are inexperienced in finance, and people who have a friend(s) who prefer to withdraw funds from the bank tend to reject CBDC and withdraw their money. People who use TV news as their primary source of information are more likely to make quicker decisions regarding CBDC.

6. Conclusions

CBDC researchers and central banks are constantly searching for the factors that influence people's decision to accept a CBDC. Researchers mostly use surveys to elicit opinions from individuals on the factors influencing their decision to accept CBDC. Our work re-investigates this issue in a unique AI-simulation environment. For the first time in literature, we use generative AI experimentation to determine the factors that influence people's decision to accept CBDC. We assessed 663 synthetic responses generated from ChatGPT 4.0 generative AI experimentation and analyzed the data using statistical methods and multinomial logistic regression techniques to assess the probability of acceptance, rejection or waiting for more information to reach a decision.

We find that (i) middle-aged and mature individuals, (ii) people who lack experience in finance, and (iii) people who earn below €75,000, are more likely to choose to wait for more information before reaching a decision on whether to accept or reject CBDC. We also find that men, earning less than €120,000, graduates, aged between 25 and 54, with friends who accept CBDCs, with no experience in finance, who get their information from Twitter, and are living in areas where merchants accept digital currencies are the ones who show more willingness to accept a CBDC. Those who use television as their main source of information decide more quickly. People who reject CBDC tend to be over 55 years old with a very high or low income. They have a medium-low level of education. They are often influenced by friends who also reject it and consume news on Twitter. In addition, cryptocurrency enthusiasts show a strong rejection, probably derived from their distrust of centralized digital currencies.

These findings are important to central banks because they provide insights into the areas where central banks need to do more work to ensure that the CBDC issue is accepted by members of the population. The insights gained from this study suggest that central banks should target the educated population, the financially literate population, and the high-income population when issuing and distributing CBDC. The findings are also significant for accelerating financial inclusion in developing countries with a large unbanked population. It offers insights into the areas central banks need to focus on to accelerate financial inclusion using CBDC. It suggests that central banks should deploy CBDC to the middle-aged and low-income unbanked population, as they may be more likely to accept CBDC. However, we must emphasize at this point that the findings may not be generalizable to an entire population due to the artificial nature of the AI-generated dataset. Therefore, we urge central banks to be cautious when interpreting and applying the results for policy implementation purposes.

This research has some limitations. One limitation of the study is that the approach used to carry out the research may not fully consider the unique economic and cultural contexts of developing economies, which could affect the design and adoption of CBDCs. We also acknowledge the limitations of AI experimentation using ChatGPT 4.0. The major limitation of generative AI experimentation using ChatGPT 4.0 is that the response data may not represent real-world situations even though the generated response data seems to mimic real-world scenarios. Another limitation of the study is the use of synthetic data, which mimics people's decisions regarding CBDC in the real world. Synthetic responses are generated based on predefined algorithms and models. The advantages of using synthetic data is that it (i) allows researchers to model and analyze potential behaviors without requiring extensive data collection, (ii) allows us to generate data that is very diverse, (iii) allows us to test diverse factors affecting CBDC acceptance decision in a variety of scenarios, and (iv) allows us to collect unique data that may be impossible to collect in real life due to the unique nature of the data. Despite these advantages, we acknowledge that synthetic data may not capture the complexities and nuances of real human decision making. As a result, it is possible to miss out on certain contextual factors, emotional influences, and unique personal experiences that can significantly impact an individual's decision to accept or reject CBDC. This limitation creates a fruitful opportunity for future researchers to explore the use of real-world human data to assess the factors affecting people's decision to accept or reject CBDC. Another limitation we should point out is that LLMs can generate responses aligned with learned patterns, which implies a possible reproduction of previous trends present in the data used for training.

Finally, we suggest additional areas for further research. Future research can re-investigate the determinants of CBDC acceptance using other AI-models, such as LLM techniques, XLNet, and LLaMA. These models may provide additional insights that could assist central banks in understanding the factors affecting CBDC acceptance. It is also interesting to use generative AI experimentation using ChatGPT 4.0 to compare the factors affecting stablecoin acceptance and CBDC acceptance since stablecoin and CBDC, despite being different, share some similarities. As a result, we have found that people who use TV news as their primary source of information are more likely to make quicker decisions regarding CBDC. Future research could involve conducting a real-world survey to compare human responses with AI-generated data, incorporating a bias analysis of the latter. Another possible line of research would be to analyze how it would influence the model if a prominent economist, a member of the central bank, or the minister of finance/economy made statements about CBDC. A final area for future research is to explore or propose CBDC design criteria that are tailored to developing economies, considering factors, such as technological infrastructure, economic stability, and cultural influences. Our expert advice on how to go about this is for central banks to consider using a two-tier or multi-tier ledger CBDC design that is delivered on distributed ledger technologies or hyperledger fabric blockchain technologies, which are robust to accommodate technological infrastructure, economic stability, and cultural differences in developing countries. Additionally, further discussions are necessary to explore the ethical implications of using synthetic responses in policymaking, ensuring transparency and accountability in decision processes.

Author contributions

Conceptualization, Sergio Luis Náñez Alonso and Peterson Ozili; methodology, Peterson Ozili and Sergio Luis Náñez Alonso; software, Sergio Luis Nañez Alonso and Beatriz María Sastre Hernández; validation, Beatriz María Sastre Hernández and Luis Miguel Pacheco; formal analysis, Sergio Luis Náñez Alonso and Beatriz María Sastre Hernández; investigation, Sergio Luis Náñez Alonso, Peterson Ozili, Beatriz María Sastre Hernández and Luis Miguel Pacheco; resources, Beatriz María Sastre Hernández; data curation, Sergio Luis Náñez Alonso and Luis Miguel Pacheco; writing—original draft preparation, Beatriz María Sastre Hernández and Luis Miguel Pacheco; writing—review and editing, Sergio Luis Náñez Alonso and Peterson Ozili; visualization, Sergio Luis Náñez Alonso and Beatriz María Sastre Hernández; supervision, Luis Miguel Pacheco and Peterson Ozili. All authors read and approved the final manuscript.

Use of AI tools declaration

In compliance with COPE guidelines, artificial intelligence (AI) has not been used for interpretation, analysis, or writing up of the final findings. The ChatGPT 4.0 language model, developed by OpenAI, has been used in this research exclusively for the generation of a dataset, in order to simulate CBDC user behavior patterns.

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Conflict of interest

All authors declare no conflicts of interest in this paper.

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