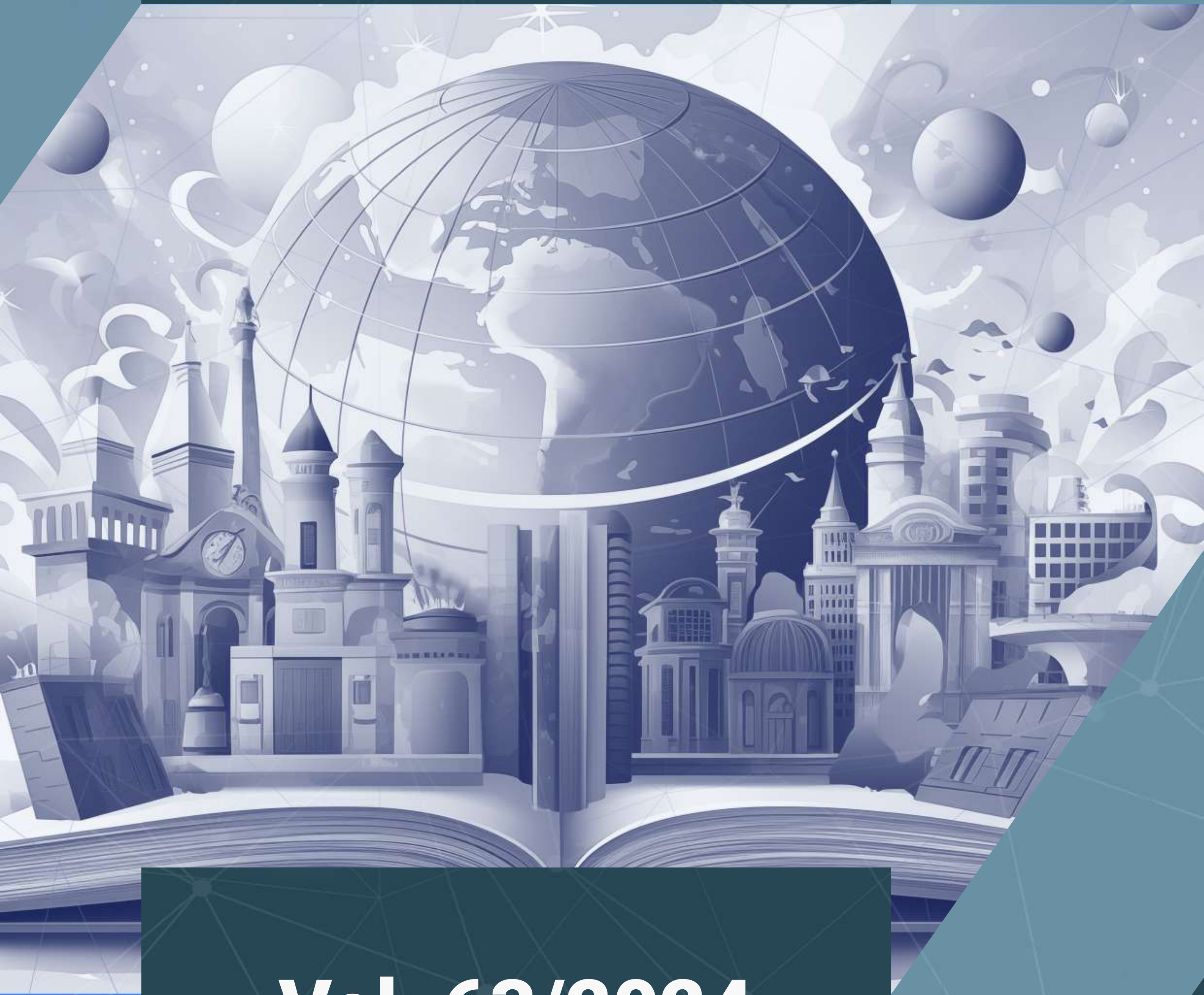
TECHNIUM
SOCIAL SCIENCES JOURNAL



Vol. 63/2024

A New Decade for Social Changes

PLUS COMMUNICATION
International Communication & PR

Technium Social Sciences Journal
Vol. 63, 184-198, November, 2024
ISSN: 2668-7798
www.techniumscience.com

Consumer Acceptance of Central Bank Digital Currency in a Fully Launched Market

Paul Golding

University of Technology, Jamaica

pgolding@utech.edu.jm

Abstract. Since 2020 the number of countries and currency unions exploring the implementation of central bank digital currency (CBDC) has increased by approximately 300 percent. The literature shows an abundance of technical feasibility studies and a dearth of research on consumer adoption. This study investigates consumer adoption of CBDC in a market (Jamaica) in which it was already launched. Data was collected from 200 respondents based on a convenience sample. A conceptual model was constructed based on the unified theory of acceptance and use of technology. To validate the model and test the six hypotheses we employed PLS-SEM partial least squares structural equation modeling. Three of the six hypotheses were supported: behavioral intention has a significant positive impact on user behavior, social influence had a significant positive impact on behavioral intention, and facilitating conditions has a significant positive impact on user behavior. Age and gender had no moderating effect. This is the first study done in a market where CBDC was implemented, done on consumers and provided jurisdictional recommendation to create network effects and increase adoption.

Keywords. Central Bank Digital Currency, Jam-Dex, Technology adoption, Jamaica

Introduction

There has been renewed interest and debate about central bank digital currencies (CBDCs). One of the recent catalysts for this debate is the advances in technology, particularly Blockchain or Distributed-Ledger-Technology (DLT) which can facilitate CBDC. Burkhard Balz (2021), a member of the Executive Board of the Deutsche Bundesbank, at the American Council on Germany, virtual event, posited that the drivers of CBDC are: The rapid pace of digitization, e-commerce, and online services due to the pandemic. These developments are increasingly calling for a safe and efficient settlement asset which can be seamlessly integrated into almost any kind of business process. The second is really a consequence of the first. Balz argues that the use of cash is waning and even in Germany the pandemic has boosted not only the use of credit and debit cards, but contactless payments.

The international Monetary Fund (IMF) Kiff et al (2020), have indicated that there is no universally accepted definition CBDC as the taxonomy of digital representation of money is still evolving. The IMF has however used a definition that this paper will accept: CBDC is a digital representation of a sovereign currency issued by and has a liability of a jurisdiction’s central bank or other monetary authority. In offering further clarification to the definition Kosse & Mattei

Technium Social Sciences Journal
Vol. 63, 184-198, November, 2024
ISSN: 2668-7798
www.techniumscience.com

(2022) offer further clarification to the definition that will be used in this paper. If the CBDC is intended for use by the public it is referred to as a "general purpose" or "retail" CBDC. As such, it offers a new option to the public for storing value and making payments. Kosse & Mattei (2022) also contrasted general purpose CBDC with other forms of existing forms of cashless payment instruments for consumers and businesses, such as credit transfers, direct debits, card payments and e-money, as it represents a direct claim on a central bank rather than the liability of a private financial institution.

In contrast to retail CBDCs, a "wholesale" CBDC targets a different group of end users – financial institutions. A wholesale CBDC is like today's central bank reserves and settlement accounts in that it is intended for the settlement of large interbank payments or to provide central bank money to settle transactions of digital tokenised financial assets in new infrastructures (Bech et al (2020) as referenced in Kosse & Mattei (2022). The authors have indicated that of the record 81 central banks surveyed in 2021, the data indicated that central banks were particularly interested in retail CBDC. This paper will therefore concentrate on retail CBDC.

The Atlantic Council (2022) an American think tank which tracks CBDC adoption by country indicated that 105 countries representing over 95% of the global gross domestic product (GDP) are exploring CBDC. This is in comparison with May 2020 when only 35 considering CBDC. Ten countries have fully launched a CBDC with Jamaica's being the first to pass legislation to have its digital currency, Jam-Dex, as legal tender.

The Bank of International Settlement (BIS 2020) has established some core features of CBDC, they include:

- Payments should be as easy as using cash, tapping with a card, or scanning a mobile phone to encourage adoption and accessibility and be able to make payments 24/7/365.
- Exchange at par with cash and should be usable in many of the same types of transactions as cash, including point of sale and person-to-person. This will include the ability to make offline transactions (for limited periods and up to predetermined thresholds).
- Payments should be at very low or no cost to end users, who should also face minimal requirements for technological investment and instant or near-instant final settlement should be available to end users
- The infrastructure should be extremely resistant to cyber-attacks and other threats. This should also include ensuring effective protection from counterfeiting.
- The system should be extremely resilient to operational failure and disruptions, natural disasters, electrical outages, and other issues. There should be some ability for end users to make offline payments if network connections are unavailable.
- The system should be able to process a very high number of transactions and be scalable to accommodate the potential for large future volumes,
- The system needs to offer sufficient interaction mechanisms with private sector digital payment systems and arrangements to allow easy flow of funds between systems.

It is important to note that a precondition for CBDC issuance is its design should not disintermediate commercial banks, nor lead to heightened volatility of banks funding sources (BIS 2020).

While the features of CBDC are homogenous the motivations for implementation are heterogeneous and based on jurisdiction. Boar and Wehrli (2021) explain that the motivations for implementations include financial stability, monetary policy implementation and financial inclusion, and payments efficiency and safety. The authors suggest that the weight given to different motivations depends on factors such as the national payment system's state of development and structure and the degree of financial inclusion in the jurisdiction. Financial inclusion emerges as a top priority for CBDC development. Payment-related motivations, such as domestic payments efficiency and payments safety are also among the top motivators for issuing general purpose CBDCs (Boar and Wehrli 2021).

The literature on CBDC is heavily skewed to the technical issues (Söilen, and Benhayoun, 2022). Kiff et al. (2020) describes an implementation process for CBDCs where the first step is to identify the needs and problems that a retail CBDC would address. Auer and Böhme (2020) propose a pyramid model for CBDC implementation. The pyramid is divided into two parts "from consumer needs' on the left-hand side to "CBDC design choices" on the right-hand side. Söilen, and Benhayoun, (2022) argue that practically all research has focused on right-hand side problems. The authors suggest that this not only illustrates a considerable research gap in the CBDC literature but shows that the process has started in the wrong end; designing different models before it is known what households and firms want.

Using the Jamaican jurisdiction and context, this paper aims at empirically investigating how customer behavior should impact the adoption of Jamaica's CBDC, Jam-Dex. The objectives include inter alia:

1. The consumers' perceptions of Jam-DexJam-Dex
2. Factors affecting the likelihood of adoption of Jam-Dex.

This article is structured as follows. Section two examines the theoretical foundations and hypothesis; section three introduces the research methodology. In section four we will report the findings, while in section five we discuss the academic and industry implications. In section six we discuss the recommendations and limitations of the study, and we will conclude in section seven.

Literature Review

Bank of International Settlements (BIS 2021) is in concert with Auer and Böhme (2020) arguing that if CBDC's are to achieve their policy goals they would need to be adopted by users and merchants. Using past payments methods to determine user needs, BIS 2021 recommended that strategies for CBDC adoption would need to be tailored to the diverse economic structures and payment landscapes in individual jurisdictions, but experience points to some common factors. Specifically, adoption may be more successful if it fulfilled unmet user needs, achieved network effects, and was implemented using existing, accessible technology and infrastructure (e.g., at the point of sale). Additional measures that some jurisdictions might consider for a potential CBDC adoption strategy include the use of CBDC by public sector authorities, requiring some minimum level of acceptance and supporting future payment needs.

Kobiruzzaman (2022) stated that technology adoption models refer to the theories and frameworks that explain why people accept and utilize modern technology. It also describes how people adopt modern technology and use it in communication, business, health, education, and other sectors. The author outlined eleven (11) models for technology adoption however for this study we will rely on Unified Theory of Acceptance and Use of Technology (UTAUT), Venkatesh et al. (2003) as the theoretical lens to examine customer related factors on the adoption of CBDC.

The theory holds that four key constructs (performance expectancy, effort expectancy, social influence, and facilitating conditions) are direct determinants of usage intention and behaviour (Venkatesh et. al., 2003). Gender, age, experience, and voluntariness of use are posited to moderate the impact of the four key constructs on usage intention and behavior (Venkatesh et. al., 2003).

The authors developed the UTAUT theory through a review and consolidation of the constructs of eight models that earlier researchers had employed to explain information systems usage and behavior. The authors saw limitations in the previous theories, mainly that the models were not empirically tested which left room for speculation on the predictive power of the constructs of each theory. Venkatesh et. al., (2003) argued that previous theories examining technology use behaviour had focused on simple systems (e.g. PC) and overlooked the use of more complex technologies, UTAUT aims was to explain the individual or user intention to use an information system and subsequent user behavior (Venkatesh et. al., 2003).

Several authors have used the theory to investigate the adoption CBDC by individual household Söilen and Benhayoun (2022); technology adoption in banking (Tarhini et al 2016; Zhou et al 2010); and e-banking (Afshan & Sharif, 2016; Baptista & Oliveira, 2015; Martins, Oliveira, & Popovič, 2014).

Hypothesis Development

The UTAUT model suggests that the actual use of technology is determined by behavioural intention. The perceived likelihood of adopting the technology is dependent on the direct effect of four key constructs, namely performance expectancy, effort expectancy, social influence, and facilitating conditions. The effect of predictors is moderated by age, gender, experience, and voluntariness of use (Venkatesh et al., 2003).

Performance expectancy (PE) was conceptually defined as the degree to which individual believes that using the system will help him or her to attain gains in job performance" (Venkatesh et al., 2003). The authors indicated that from a theoretical point of view PE may differ according to gender and age. For this study's purposes (PE) means users will prefer Jam-Dex to traditional currency due to its usefulness as it makes conducting transactions faster, more convenient, and increases customer service efficiency. This would include 24/7 availability, reducing payment and settlement time, reducing transaction cost, and simplifying the transaction process (Song and Wang 2022). In several studies, PE has been found to be the strongest predictor of use intention and is significant in both voluntary and mandatory settings (Zhou, Lu & Wang, 2010; Venkatesh, Thong & Xu, 2016, Kabra, Ramesh, Akhtar, & Dash, 2017; and Salloum, Al-Emran, Shaalan & Tarhini, 2018. We therefore posit that:

H1: Performance expectancy positively affects the behaviour intention to use Jam-Dex.

Effort expectancy is defined as "the degree of ease associated with the use of the system" (Venkatesh et al., 2003). This construct is similar to the perceived ease of use from the Technology Acceptance Model (TAM). Carter and Belanger (2004) explain that effort expectancy provides the measurement of a system's interface design, ease of use, flexibility, and ease of learning. This suggests that if users feel that Jam-Dex is easy to use and does not require much effort they will intentionally use the digital currency in the future. This would include whether Jam-Dex is easy to obtain and whether learning to use Jam-Dex is easy and convenient for users. In many studies effort expectancy has had a significant impact on intention to use (Chen & Hwang, 2019; Kabra et al., 2017 Karadağ, & Orhan, 2015). The effect of effort expectancy diminishes over time and becomes non-significant after extended usage of the technology (Gupta, Dasgupta & Gupta, 2008; Chauhan & Jaiswal, 2016). We therefore posit that:

H2: Effort expectancy: positively affects the behaviour intention to use Jam-Dex

Social influence is defined as "the degree to which an individual perceives that important others believe he or she should use the new system" (Venkatesh et al., 2003). Social influencers include the opinions of the potential uses of friends, relatives, and superiors (Lopez-Nicolas et al 2008). This suggests that if potential users have many friends, relatives, colleagues, and competitors using Jam-Dex, this will increase their willingness to accept it. The effect of social influence is significant when the use of technology is mandated (Venkatesh et al., 2003). In the mandatory context, individuals might use technology due to compliance requirement, but not personal preferences (Venkatesh & Davis, 2000). Several studies have shown that social influences have a significant impact on intention to use (Durak, 2018; Zhou, Lu, & Wang, 2010). We therefore posit that:

H3: Social influences positively affect the behaviour intention to use Jam-Dex.

According to the initial Theory of Reasoned Action, (Ajzen & Fishbein 1980) an intention to engage in a certain behavior is considered the best predictor of whether a person engages in that behavior. Intentions, in turn, are predicted by attitudes and subjective norms. That is, the more positively a person regards a certain behavior or action and the more they perceive the behavior as being important to their friends, family, or society, the more likely they are to form intentions to engage in the behavior. Several studies have shown that a user's intention to use a technology will determine his or her usage behaviour (Söilen and Benhayoun 2022; Solekah and Hilmawan, 2021; Purwanto and Loisa 2021). We therefore posit:

H4: Behavioural intention to use Jam-Dex will positively affect the user behaviour regarding usage

Facilitating conditions is "the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system" (Venkatesh, 2003). This would include making Jam-Dex available to the public, across regions, available 24/7, available offline which is like cash and implemented with the use of existing technology, like point of sale. Venkatesh et al., (2003) argued that facilitating conditions have a direct positive effect on intention to use, but after initial, the effect becomes non-significant. We therefore posit that:

H5: Facilitating conditions positively influence the use behaviour of Jam-Dex

Holmes and Rempel (1985) defined trust as people's abstract positive expectations that they can count on partners to care for them and be responsible for their now and in the future. Gefen (2000) mentioned an expanded definition to include technology and electronic commerce: Trust is also considered by researchers as a complex human belief that is formed through the interaction between human and non-human agents and influenced by technological, social, and behavioral organizational aspects. Venkatesh et al., (2003) suggest that trust is increased by means of effort expectancy that indicates the cognitive efforts needed to utilize the technology. Due to this effort expectancy, the user assumes the technology provider is investing in the relationship by making it easily accessible (Gefen et al 2003). Friedman et al (2000) argued that trust influences a user's intention to use online payment systems to provide personal information to an online store by creating positive feelings about the expected outcome, thus transforming uncertain future actions

Technium Social Sciences Journal
Vol. 63, 184-198, November, 2024
ISSN: 2668-7798
www.techniumscience.com

into certain ones. Accordingly, users of Jam-Dex would feel comfortable that the transaction system is reliable and capable of conducting secure transactions. We therefore posit that:

H6: Effort Expectancy has an indirect impact on use behavior through trust.

According to Venkatesh et al., (2003) the interactive effect of some constructs with personal and demographic factors demonstrates the complexity of the technology acceptance process, which is dependent on individuals' age, and gender. Age moderates the effect of all four predictors. Gender affects the relationships between effort expectancy, performance expectancy and social influence. (Venkatesh et al., 2003).

Method

The aim of the present research is to examine individual acceptance of Jam-Dex, Jamaica's central bank digital currency by using the unified theory of acceptance and use of technology. A conceptual model was constructed based on prior empirical research. To validate the model a questionnaire was adapted from previous literature. Structural equation modeling (SEM) was used to test the research hypothesis. This section details a description of the methods used in the research.

In the data collection process, a questionnaire adapted from Söilen and Benhayoun (2022). The questionnaire consisted of 25 questions, divided into two sections. The first section had 10 questions which measured the main study variables (performance expectancy, effort expectancy, social influence, facilitating conditions, trust in Jam-Dex and behavioural intentions. All items in this section were measured using a 5-point Likert type scale ranging from 1 (strongly disagree") to 5 ("strongly agree"). The second section was used to collect sociodemographic characteristics of the study sample, including age, gender, level of education, and current interactions with commercial banks.

At the time of data collection, June 2022, the tail of social distancing under COVID-19 was still in effect, therefore a convenience sample was utilized. The survey was conducted online. The survey link was made available through the researcher's various social media networks in a non-professional and professional capacity. The exclusion restriction to complete the survey was age 18 years or older and resident in Jamaica.

For data analysis we employed PLS-SEM partial least squares structural equation modeling to analyze the proposed research model, specifically Smart PLS 4. SEM is suitable for large and small sample size and non-normal data (Hair et al 2017) and is fit for exploratory research (Peng and Lai 2012).

Results

Descriptive

We received two hundred (200) responses with a gender breakdown of 60 percent female and 40 percent male. Age analysis indicates that approximately seventy percent is in the age range 21 – 50: 49 percent of the respondents were in the age range 21 – 36 followed by 27 percent in the age range 36 – 50 and 12 percent each for ages groups 51 – 65 and under 20. The respondents were highly educated about 50 percent had a bachelor's degree, 19 percent had a master's degree, and another 17 percent had a diploma. The employments status 65 percent were full-time employed followed by 16 percent students; the other categories were all below double digits. The social status of the respondents was concentrated in the working and middle class: 38 percent describe

Technium Social Sciences Journal
Vol. 63, 184-198, November, 2024
ISSN: 2668-7798
www.techniumscience.com

themselves as middle class, 35 percent as working class followed by 13 percent as lower middle class.

Model Evaluation

The proposed model was evaluated in two steps: (1) the measurement model evaluation (outer model) and (2) the structural model (inner model).

Measurement Model

Confirmatory Factor Analysis (CFA) was performed to validate the measurement model (outer model) by examining the relationship between the indicators and their underlying construct and the structural model (testing the hypothesized relationships). The variable's convergent validity is examined using the average variance extracted (AVE), composite reliability (CR), and factor loadings (outer loadings). The acceptable value of outer loadings is a minimum of 0.7, AVE minimum of 0.5 and CR value minimum of 0.7 (Hair et al., 2010).

The model had no convergent validity or composite reliability issues as AVE for all the factors exceeded the threshold of 0.5, and CR exceeded the threshold of 0.7 (see table 1). Figure 1 shows the run of the PLS Algorithm.

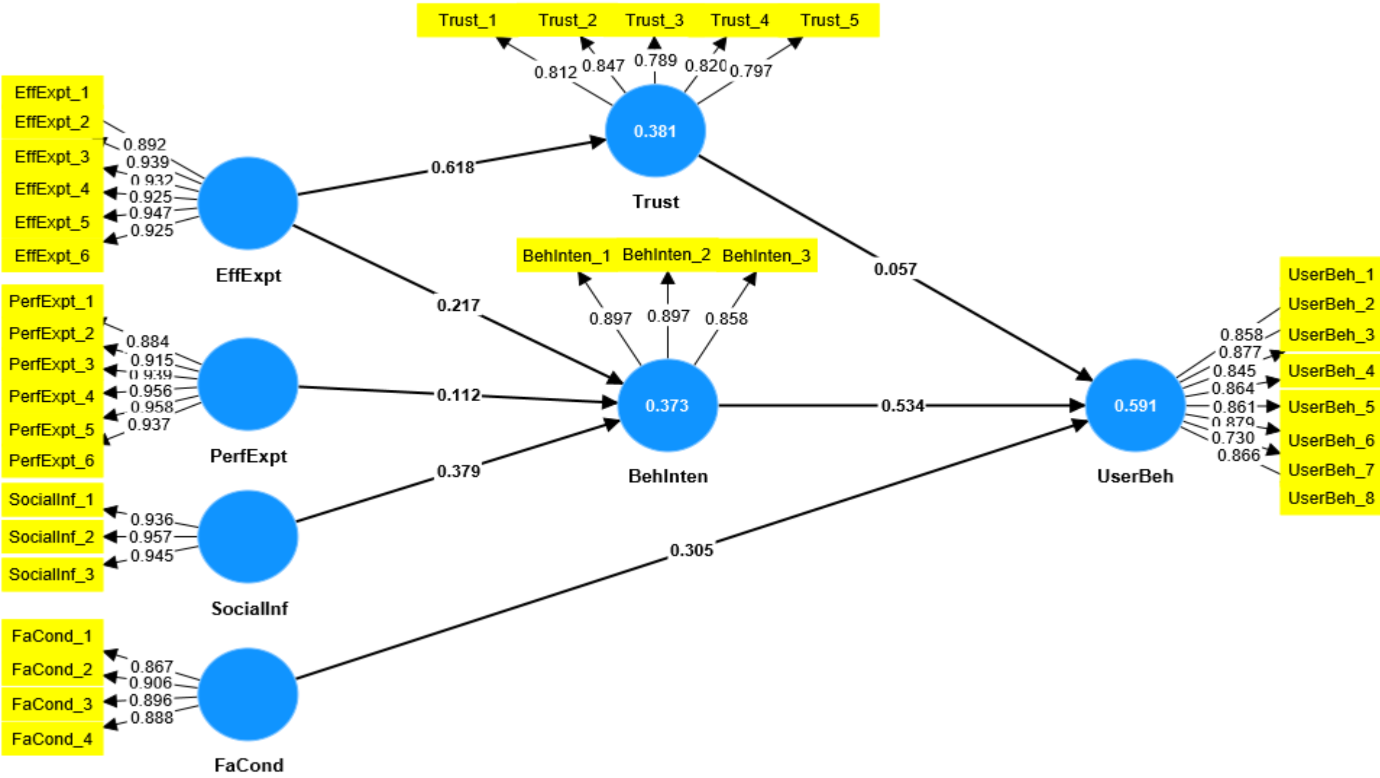
Table I: *Reliability and Validity of Constructs*

Constructs	Indicator	Loadings	AVE	CR
Behavior Intention	BI1	0.897	0.782	0.915
	BI2	0.897		
	BI3	0.858		
Effort Expectancy	EE1	0.892	0.859	0.973
	EE2	0.939		
	EE3	0.932		
	EE4	0.925		
	EE5	0.947		
	EE6	0.925		
Facilitating Conditions	FC1	0.872	0.790	0.938
	FC2	0.907		
	FC3	0.895		
	FC4	0.881		
	PE1	0.884		
Performance Expectancy	PE2	0.915	0.868	0.975
	PE3	0.939		
	PE4	0.956		

	PE5	0.958		
	PE6	0.937		
Social Influence	SI1	0.936	0.895	0.962
	SI2	0.957		
	SI3	0.945		
Trust	T1	0.812	0.662	0.907
	T2	0.847		
	T3	0.789		
	T4	0.820		
	T5	0.797		
Use Behavior	UB1	0.857	0.720	0.954
	UB2	0.877		
	UB3	0.845		
	UB4	0.864		
	UB5	0.863		
	UB6	0.876		
	UB7	0.734		
	UB8	0.865		

Note: AVE (Average Variance Extracted) = (summation of the square of the factor loadings) / {(summation of the square of the factor loadings) + (summation of error variance)}; Composite Reliability (CR) = (square of the summation of the factor loadings)/ {(square of the summation of the factor loadings) + (summation of error variance)}. (Barker & Ong, 2016)

Figure I: Measurement Model



Next discriminant validity was examined to assess how distinct each variable was from other variables. The Heterotrait-monotrait ratio (HTMT) and the square root of the average variance derived for each construct (Fornell and Larcker Criterion) were used to test the discriminant validity (Kline, 2016). Discriminant validity was established as no value exceeded the maximum threshold of 0.85. See table II and III.

Table II: *Heterotrait-Monotrait Ratio (HTMT) Analysis for Checking Discriminant Validity of Inner Model*

	BI	**EE**	**FC**	**PE**	**SI**	**T**	**UB**
BI							
EE	0.553						
FC	0.521	0.823					
PE	0.507	0.748	0.701				
SI	0.617	0.578	0.599	0.541			
T	0.683	0.658	0.675	0.593	0.717		
UB	0.787	0.654	0.629	0.581	0.595	0.613	

Note: BI – Behavioral Intention, EE – Effort Expectancy, FC – Facilitating Conditions, PE – Performance Expectancy, SI – Social Influence, T – Trust, UB – Use Behavior

	BI	EE	FC	PE	SI	T	UB
BI	**0.884**						
EE	0.507	**0.927**					
FC	0.469	0.842	**0.889**				
PE	0.466	0.724	0.656	**0.932**			
SI	0.556	0.552	0.557	0.519	**0.946**		
T	0.594	0.617	0.612	0.555	0.65	**0.813**	
UB	0.711	0.625	0.59	0.557	0.561	0.562	**0.849**

Table III: Fornell-Larcker Criterion Analysis for Checking Discriminant Validity of Construct
Note: BI – Behavioral Intention, EE – Effort Expectancy, FC – Facilitating Conditions, PE – Performance Expectancy, SI – Social Influence, T – Trust, UB – Use Behavior

Structural Model

With the reliability and validity of the constructs established in the measurement model we continue to the second step, the structural model. To evaluate the structural model in accordance with PLS-SEM, the following steps must be completed.

Firstly, the collinearity will be determined, the path coefficients will be tested for direct relationships and moderation effect, the coefficient of determination will be evaluated (R^2 value), and the effect size (f^2) will be evaluated.

Multi-collinearity occurs when two or more exogenous variables in a regression model have a significant relationship (Block, Miller, & Wagner, 2014). This creates difficulty in interpreting the regression analysis as the researcher is unlikely to determine the effects of each individual independent variable on the dependent variable (Hair, Black, Babin, Anderson, & Tatham, 2010). The threshold for the absence of multi-collinearity is where variance inflation factor (VIF) value for each variable is less than 5. Table IV indicates that VIF for each of the constructs is less than, hence the absence of multi-collinearity is established.

Table IV: *Collinearity and Common Method Bias Assessment of Inner Model*

Indicators	**VIF**	**Collinearity Problem (VIF>5)?**
BI	1.546	No
EE	4.227	No
FC	3.624	No
PE	2.215	No
SI	1.556	No
T	1.546	No

Note: BI – Behavioral Intention, EE – Effort Expectancy, FC – Facilitating Conditions, PE – Performance Expectancy, SI – Social Influence, T – Trust, UB – Use Behavior

Assessment of Structural Model

To test the proposed hypotheses of this study, the structural model evaluation was conducted using a bootstrapping approach (Zhao, Lynch, & Chen, 2010). The results indicated that three of the six hypotheses with direct and indirect effect were supported: Social Influence has a significant positive impact on Behavioral Intention; Behavioral Intention has a significant positive impact on Use Behavior; and Facilitating Conditions has a significant positive impact on Use Behavior. See tables V and VI

Table V: *Summary of the Direct Effects*

Hypotheses	Relationship	Beta	SE	t-value	p-value	Statistic Decision
H1	PE -> BI	0.093	0.087	0.489	0.625	Not – Supported
H2	EE -> BI	0.071	0.077	0.318	0.750	Not – Supported
H3	SI -> BI	0.43	0.431	3.335	0.001	Supported
H4	BI -> UB	0.534	0.535	8.327	0.000	Supported
H5	FC -> UB	0.313	0.311	4.681	0.000	Supported

Note: BI – Behavioral Intention, EE – Effort Expectancy, FC – Facilitating Conditions, PE – Performance Expectancy, SI – Social Influence, T – Trust, UB – Use Behavior.

Table VI: *Summary of the Indirect Effect*

Hypotheses	Relationship	Beta	SE	t-value	p-value	Statistic Decision
H6	EE -> T -> UB	0.026	0.026	0.551	0.582	Not – Supported

Note: EE – Effort Expectancy, T – Trust, UB – Use Behavior

The coefficient of determination (R^2) was evaluated to measure how well the model predicts the use of JamDex. The model without moderation effect adequately accounts for moderate level of variation in Behavioral Intention as shown Table VII, with R^2 of 0.373 or 37%. The model also accounts for substantial variation in Use Behavior with R^2 of 0.591 or 59%. These indicate that the model fit without moderation predicted are moderate. Whereas, with the moderation effect of age and gender the model accounts for 0.381 or 38% variation in Behavioral Intention. In the case of Use Behavior, R^2 is 0.614 with the moderation effect of Age and Gender which shows the model moderately accounts for 61% variation in Use behavior. According to these results, the predicted model fit is moderate for Behavior Intention and Use Behavior towards Jam-Dex, both with and without moderation effects.

Table VII: *R^2 of Endogenous Latent Variables*

Construct	R^2	With Moderation	Result
BI	0.373	0.395	Moderate
UB	0.591	0.614	Moderate

Note: BI – Behavioral Intention, T – Trust, UB – Use Behavior

Assessment of Moderation Analysis

Table VII presents a summary of the moderation relationships of age and gender between key factors with Behavioral Intention and Use Behavior. These moderating effects provide insight into the ways in which specific factors interact to shape respondents' intentions to use Jam-Dex. The statistically significant t-values and p-values show that all of the hypotheses with respect to these moderation effects are not supported.

Technium Social Sciences Journal
Vol. 63, 184-198, November, 2024
ISSN: 2668-7798
www.techniumscience.com

Table VIII *Summary of the Moderation Effect*

Hypotheses	Relationship	Beta	SE	t-value	p-value	Statistic Decision
H7	Age x SI -> BI	-0.087	-0.083	1.096	0.273	Not – Supported
H8	Age x FC -> UB	-0.081	-0.079	1.826	0.068	Not – Supported
H9	Age x PE -> BI	-0.032	-0.012	0.29	0.772	Not – Supported
H10	Age x EE -> BI	0.129	0.101	1.159	0.246	Not – Supported
H11	Gen x SI -> BI	-0.06	-0.057	0.36	0.719	Not – Supported
H12	Gen x EE -> BI	0.171	0.179	0.687	0.492	Not – Supported
H13	Gen x PE -> BI	0.032	0.025	0.145	0.885	Not – Supported

Note: BI – Behavioral Intention, EE – Effort Expectancy, FC – Facilitating Conditions, PE – Performance Expectancy, SI – Social Influence, T – Trust, UB – Use Behavior

Assessment of the Effect Size (f^2)

The Effect size (f^2) is utilized to calculate the change in coefficient of determination (R^2) and evaluate if a certain independent variable had a significant impact on dependent variable. It shows that the changes in Coefficient of determination R^2 were observed when a specific independent variable is left out of the model.

A predictor or independent latent variable's impact size f^2 of 0.02 indicate small effect, 0.15 indicate medium effect, and 0.35 indicate large effect, this can be used as a criterion to determine what level of effect it has at the structural level (Hair et al., 2017). Table IX shows the effect size of this study that explains the effect sizes of all independent variables such as Effort Expectancy, Facilitating Conditions, Performance Expectancy, Social Influence, Trust on Behavioral Intention and Use Behavior.

Table IX: The Effect Size of the Model

Latent variables	F^2	Result
BI -> UB	0.464	Large
EE -> BI	0.001	Small
FC -> UB	0.154	Medium
PE -> BI	0.001	Small
SI -> BI	0.074	Small
Trust -> UB	0.002	Small

Note: BI – Behavioral Intention, EE – Effort Expectancy, FC – Facilitating Conditions, PE – Performance Expectancy, SI – Social Influence, T – Trust, UB – Use Behavior

Discussion

The Atlantic Council Tracker indicates that 134 countries and currency unions representing 98 percent of global GDP are exploring CBDC. In May 2020 that number was only 35 (Central Bank Digital Currency Tracker). The motivations for the surge in CBDC interest have been attributed to several factors including the rapid pace of digitization, e-commerce and online services due to the pandemic. There is also the belief that the use of cash is waning with the increased use of credit and debit and the popularity of contactless payments.

Despite the surge in interest in CBDC only three countries have fully launched digital currency, Bahamas, Nigeria and Jamaica. In 2022 Jamaica amended the Bank of Jamaica Act to include a digital form of the Jamaican Dollar and subsequently on July 11, 2022, Jamaica's digital currency Jan-Dex was launched. The data for this study was collected during the lead-up to the launch. Consequently, respondents had a relatively high level of exposure 71 percent and 76 percent had some knowledge of Jam-Dex.

The result of this study indicates that behavioral intention has a significant positive impact on user behavior (H4), social influence has a significant positive impact on behavioral intention (H3) and facilitating conditions has a significant positive impact on user behavior (H5). These findings are consistent with Söilen et al, (2022) who found behavioural intentions, social influences or social recommendations. and the existence of facilitating conditions foster the continuous adoption of CBDCs by households.

The findings of this study did not support performance expectancy in enhancing adoption of Jam-Dex/CBDC, while the Söilen et al (2022) did. This study did support effort expectancy in enhancing Jam-Dex adoption nor did effort expectancy have any indirect effect on user behaviour through trust. Söilen et al (2022) findings were consistent with this study as it relates to the direct effect but not with the indirect effect. Gender and age did not affect the direction and/or strength of the relationship on any of the constructs.

Other researchers have promoted the importance of trust in facilitating adoption of CBDC Söilen et al (2022) and Bijlsma et al (2021). The apparent inconsistency between this study and previous may not surprising as BIS 2021 recommended that strategies for CBDC adoption would need to be tailored to the diverse economic structures and payment landscapes in individual jurisdictions. Further studies are required to determine if other jurisdictions are consistent with Jamaica or if this is an aberration.

Recommendations

To enhance the adoption of Jam-Dex/CBDC it is necessary for both end-users and merchants to accept them. Tan (2023) found that there is a feedback loop where more households will adopt CBDC if more firms accept CBDC and vice versa - incentivizing both households and firms will result in greater levels of take-up. In Jamaica merchants have indicated that there are no incentives to use Jam-Dex. This is supported by data where the total number of customers in February 2023 was 190,000, while total value of Jam-Dex transactions in 2022 was $357 million, which is less than 0.01 of the currency in circulation (Muir 2022). A significant facilitating condition is to provide lower cost to both merchants and customers to adopt Jam-Dex.

The Jamaican government has a social program known as Programme of Advancement Through Health and Education (PATH). This is a Conditional Cash Transfer Programme targeting vulnerable households in the population. According to the Ministry of Labour and Social Security there are approximately 350,000 beneficiaries. The government indicated that PATH benefits will be paid via Jam-Dex, but this has not happened yet. Paying Path via Jam-Dex would achieve two objectives, increase the adoption and increase digital inclusion.

Emergency online classes, which was a feature of the pandemic, has increased digital access and use in Jamaica. With the population having increased internet access, social media like TikTok and social media influencers should be included in the marketing strategy to increase the adoption of Jam-Dex. This strategy would be consistent with the findings which indicated that social influence would drive adoption.

Limitations

To my knowledge, this is the first paper to examine the adoption of digital currency in an environment where it was launched. The data analysis was robust, the findings are intriguing, and differ from some earlier ones. Despite the strengths of this paper there are some limitations. The data was collected during lockdown; therefore, convenience sampling techniques were applied. Along with sample size of 200 respondents, this limits the generalizability of the findings. The sample was comprised mainly of highly educated respondents who would be digitally literate and more likely to know about Jam-Dex. Future research should include a representative sample which would be more generalizable.

Conclusion

While only three countries have fully launched CBDC, since 2020 the number of countries and currency unions exploring its implementation has risen from 35 to 134 in 2024, representing 98 percent of global GDP. The initial motivation for adoption was cryptocurrency, however since then the COVID pandemic other factors have come into focus including increased e-commerce activities, cashless payments, social distancing, creating programmable money and the elusive promotion of financial inclusion. The motivations for each country or groups of countries will largely depend on economic conditions. With so many countries at various stages of development the future of money is decidedly digital and CBDC.

At the outset of CBDC, the focus was on technical feasibility and ensuring that retail banks were not disintermediate or caused volatility in the sector. This proof of concept has been shown to be feasible, but adjustments are needed for each jurisdiction. The focus now must be on adoption and creating network effects to increase abortion so that policy objectives can be achieved.

References

[1] Atlantic Council https://www.atlanticcouncil.org/cbdctracker/ retrieved September 30, 2022
[2] Auer R., and Böhme R. (2020) The technology of retail central bank digital currency BIS Quartely Review
[3] Bank of International Settlement (BIS 2020) https://www.bis.org/publ/othp33.pdf
[4] Bech, M, J Hancock, T Rice and A Wadsworth (2020): "On the future of securities settlement", BIS Quarterly Review, March, pp 67–83
[5] Boar C., and Wehrli A. (2021) Ready, steady, go? – Results of the third BIS survey on central bank digital currency https://www.bis.org/publ/bppdf/bispap114.pd
[6] Burkhard Balz: Central bank digital currencies – the future of money? Speech by Mr Burkhard Balz, Member of the Executive Board of the Deutsche Bundesbank, at the American Council on Germany, virtual event, 10 February 2021. https://www.bis.org/review/r210211e.pdf
[7] Kiff J., Alwazir J., Davidovic S., Farias A., Khan A., Khiaonarong T., Malaika M., Monroe H., Sugimoto N., Tourpe H., and Zhou P, (2020) IMF Working paper: A Survey of Research on Retail Central Bank Digital Currency
[8] Kosse A., and Mattei L., (2022) BIS Papers No 125 Gaining momentum – Results of the 2021 BIS survey on central bank digital currencies. https://www.bis.org/publ/bppdf/bispap125.pdf

Technium Social Sciences Journal
Vol. 63, 184-198, November, 2024
ISSN: 2668-7798
www.techniumscience.com

[9] Marikyan, D. & Papagiannidis, S. (2021) Unified Theory of Acceptance and Use of Technology: A review. In S. Papagiannidis (Ed), TheoryHub Book. http://open.ncl.ac.uk

[10] Söilen S. K., and Benhayoun L., (2022): Household acceptance of central bank digital currency: the role of institutional trust. International Journal of Bank Marketing, ISSN 0265-2323, E-ISSN 1758-5937, Vol. 40, no 1, p. 172-196

[11] Venkatesh, Viswanath; Morris, Michael G.; Davis, Gordon B.; and Davis, Fred D. 2003. "User Acceptance of Information Technology: Toward a Unified View," MIS Quarterly, (27: 3).

[12] Martha Muir JULY 20 2023 Jamaica, we have a CBDC. Financial Times https://www.ft.com/content/91ac9f03-1ff8-47c9-bd0f-64449e2159d8

[13] Tan B (2023) Central Bank Digital Currency Adoption: A two-sided Model, International Monetary Fund. https://www.imf.org/en/Publications/WP/Issues/2023/06/16/Central-Bank-Digital-Currency-Adoption-A-Two-Sided-Model-534325

[14] Barker, R., & Ong, D. (2016). A measurement scale for students' usage of online networks. *Perspectives in Education*, *34*(2), 1-18.

[15] Block, J. H., Miller, D., & Wagner, D. (2014). Bayesian methods in family business research. *Journal of Family Business Strategy*, *5*(1), 97-104.

[16] Chin, W. W. (1998). The partial least squares approach to structural equation modeling. *Modern methods for business research*, *295*(2), 295-336.

[17] Côrte-Real, N., Oliveira, T., & Ruivo, P. (2017). Assessing business value of Big Data Analytics in European firms. *Journal of Business Research*, *70*, 379-390.

[18] Duarte, P. A. O., & Raposo, M. L. B. (2010). A PLS model to study brand preference: An application to the mobile phone market. *Handbook of partial least squares: Concepts, methods and applications*, 449-485.

[19] Hair Jr, J. F., Hult, G. T. M., Ringle, C., & Sarstedt, M. (2017). A primer on partial least squares structural equation modeling (PLS-SEM). Sage Publications.

[20] Hair, J. F, Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (2010). Multivariate Data Analysis (7th ed.). New Jersey: Prentice Hall.

[21] Hair, J. F, Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2014). A Primer on Partial Least Squares Structure Equation Modelling (PLS). California, USA: Sage Publications Ltd.

[22] Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). Multivariate Data Analysis (7th ed.; Upper Saddle River, Ed.). New Jersey: Prentice Hall.

[23] Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of e-Collaboration (ijec)*, *11*(4), 1-10.

[24] Moksony, F., & Heged, R. (1990). Small is beautiful. The use and interpretation of R2 in social research. *Szociológiai Szemle, Special issue*, 130-138.

[25] Zhao, X., Lynch Jr, J. G., & Chen, Q. (2010). Reconsidering Baron and Kenny: Myths and truths about mediation analysis. *Journal of consumer research*, *37*(2), 197-206.