

Exploratory Factor Analysis on Determinants of the Waqf Blockchain Ecosystem among Millennial Public University Alumni in Malaysia

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DOI: <https://doi.org/10.47772/IJRISS.2026.100900179>

Received: 16 September 2026; Accepted: 21 September 2026; Published: 05 October 2026

ABSTRACT

Purpose: This study aims to develop a measurement instrument for the Waqf Blockchain Ecosystem (Waqfchain) and to establish the underlying factor structure of that instrument using the Unified Theory of Acceptance and Use of Technology among millennial public university alumni in Malaysia. Based on past research, UTAUT hypothesises four variable constructs: performance expectancy, effort expectancy, social influence and facilitating conditions. These characteristics are predictive of behavioural intent. This study adds smart contract as a fifth exogenous construct and retains voluntariness of use as the sole moderator in place of the four moderators originally proposed.

Design/methodology/approach: A total of 150 pilot questionnaires were distributed to millennial alumni of Malaysian public universities, returning 106 responses, of which 87 were usable after univariate and multivariate outlier screening. Following normality and multicollinearity checks, exploratory factor analysis using principal component extraction, with varimax rotation where more than one component emerged, was applied separately to each of the seven constructs measured on a ten-point interval scale. The choice of principal component extraction for item screening is justified explicitly, and Cronbach's alpha and attenuation-corrected inter-construct correlations were then examined.

Findings: Six constructs, namely performance expectancy, effort expectancy, social influence, facilitating conditions, smart contract and behavioural intention, resolved into a single component, while voluntariness of use resolved into two. Effort expectancy, social influence and behavioural intention required no item reduction, whereas performance expectancy, facilitating conditions, smart contract and voluntariness of use did. KMO values for all constructs exceeded 0.50, ranging from 0.776 to 0.875, and every Bartlett's test of sphericity was significant at $p < .001$. Total variance explained ranged from 51.922% to 67.631% and Cronbach's alpha from 0.812 to 0.908. Within-construct dimensionality and internal consistency were therefore satisfactory. Discriminant validity, however, was not established at the pilot stage: correlations between effort expectancy and social influence ($r = .894$) and between voluntariness of use and behavioural intention ($r = .872$) approach unity once corrected for attenuation.

Research limitations/implications: The pilot sample of 87 respondents is modest and concentrated in Malaysia's urban central region, and responses reflect anticipated rather than observed use of a platform that has not yet been deployed. The factor structure and, in particular, discriminant validity must be confirmed through confirmatory factor analysis on an independent field sample before the instrument is used for structural hypothesis testing.

Originality/value: This study addresses a gap in the blockchain-based waqf literature by developing and screening a measurement instrument that treats smart contract as a distinct exogenous construct and voluntariness of use as a moderator, and by identifying the specific measurement issues that the confirmatory stage must resolve.

Keywords: Waqf blockchain, Smart contract, Exploratory factor analysis, Millennial alumni, UTAUT

INTRODUCTION

Waqf, an enduring Islamic philanthropic institution, has historically played a pivotal role in promoting social welfare and economic stability within Muslim societies. It involves the endowment of assets or properties for charitable purposes, with the benefits being distributed to the community while the original asset is preserved in perpetuity (Mohsin, 2013). The historical annals record that since the advent of Islam, waqf has contributed significantly to the development of higher education. Al-Azhar, Al-Qarawiyyin and Halawabin are examples of higher educational waqf institutions that ran efficiently for centuries on endowment income alone. In Malaysia, waqf has been widely utilised to fund educational institutions, healthcare and community development projects, and numerous public universities have initiated waqf funds supported by a mix of traditional and modern fundraising mechanisms.

Despite this potential, the institution has not reached the critical mass required to become self-sustaining. Usman and Ab Rahman (2023) report that Malaysian public universities continue to operate waqf funds that are too small to materially offset operating costs, while Mohsin and Muneeza (2018) attribute the shortfall to a low level of efficiency, transparency and accountability in the management of waqf funds, conditions which suppress the realisation of waqf's potential. Mohaiyadin et al. (2022) document the same pattern within the specific setting of Malaysian public universities, reporting that accountability and transparency problems in the collection and distribution of waqf funds are compounded by legal complexity, the absence of standardised accounting systems and limited disclosure at every stage of administration. These weaknesses have proven resistant to incremental reform.

A second constraint is conceptual rather than administrative. A persistent misconception treats waqf as necessarily immovable, taking the form of land or buildings, which depresses participation among contributors who hold no such assets. Most Muslim jurists have accepted the concept of cash waqf, and cash waqf as movable property is precisely the instrument that opens endowment to a salaried, urban and digitally native population. Yet recent research finds that Malaysian Muslims still exhibit low cash waqf awareness, which suggests the necessity of using current technologies to promote cash waqf more effectively and efficiently.

Blockchain technology, with its inherent features of transparency, immutability and decentralisation, has emerged as a promising response to both constraints. Blockchain is a distributed peer-to-peer network that permits non-trusting parties to transact without a trusted intermediary to verify the transaction, and the second generation of the technology allowed more complex transactions by carrying computation over the network. Applied to endowment, blockchain enables the digitisation of waqf through smart contracts, ensuring the integrity of waqf transactions and fostering trust among stakeholders. The concept of Waqfchain integrates blockchain into waqf administration, offering a framework for collecting, distributing and monitoring waqf funds such that it executes donor intent without exposure to bureaucratic delay or administrative discretion (Zulaikha and Rusmita, 2018; Al-Daihani et al., 2023).

Blockchain can build trust in waqf institutions and ensure accountability (Mohsin and Muneeza, 2018), and estimates of the global potential of waqf reach around one trillion United States dollars, with land waqf assets exceeding three trillion. Some donors withhold contributions simply because they do not believe in the waqf trustee. Integrating blockchain technology with waqf is expected to narrow the gap between the potential and the realisation of waqf funds. However, empirical research on blockchain-based waqf adoption remains scarce, and the application of the waqf blockchain still needs to be improved in several countries because it is bound to different regulations in each jurisdiction (Zulaikha and Rusmita, 2018; Taherdoost, 2022).

The population of interest for this study is the millennial alumni of a Malaysian public university. The high growth of internet and smartphone users has resulted in the emergence of various digital start-ups, and those innovations have changed habits, including online donation. Millennials are projected to dominate seventy-five per cent of the Malaysian workforce, yet today's digital waqf platforms have not successfully cultivated waqf in this community. Alumni occupy a doubly relevant position, being at once philanthropic donors with an affiliation to the institution and technology adopters with the digital fluency to use a blockchain-based platform. This intersection remains largely unexamined.

Before any structural claim about adoption can be made, the instrument used to measure that adoption must itself

be established. This article therefore reports the measurement development stage of a larger programme of research. It develops a scale for the Waqf Blockchain Ecosystem grounded in the Unified Theory of Acceptance and Use of Technology, extends that theory with smart contracts as an additional exogenous construct, retains voluntariness of use as the sole moderator, and subjects the resulting item pool to exploratory factor analysis and reliability analysis on pilot data. The purpose is to determine the underlying dimensionality of each construct, to identify items that fail to load adequately on their intended factor, and to deliver a parsimonious and psychometrically defensible instrument for subsequent confirmatory testing.

LITERATURE REVIEW

UTAUT has been widely applied in prior research on payment and banking technologies. Alkhowaiter (2020) applied UTAUT to explore the adoption of digital payment and banking methods across Gulf countries and found performance expectancy to be a consistent predictor of intention. Soomro (2019) combined UTAUT with religiosity as a moderator to understand the adoption of a newly introduced payment system among Saudi banking customers. Baabdullah et al. (2019) found that consumer perception of ease of use positively influences behavioural intention toward mobile banking services, and Venkatesh et al. (2012) extended the original formulation into UTAUT2 for consumer contexts.

Within the blockchain domain the literature is considerably thinner and less settled. Taherdoost (2022), in a critical review of blockchain acceptance models, notes that blockchain adoption frameworks remain fragmented and inconsistent across studies, without a single dominant, empirically settled model of the kind that TAM or UTAUT provides for general technology adoption. Shrestha et al. (2021), who augmented TAM with trust constructs for a blockchain-based system, found that relationships between trust-related predictors and adoption intention varied according to the specific type of blockchain system under study rather than following one universal direction. Within Islamic social finance the position is thinner still. Aloui, Hammami and Sarwar (2021) survey the application of blockchain across Islamic finance and report a literature dominated by conceptual proposals rather than tested models, Abdullah, Hassan and Rahman (2022) reach a similar conclusion for Islamic social finance specifically, Zulaikha and Rusmita (2018) set out an early architecture for blockchain-based waqf management, Mohaiyadin et al. (2022) examined accountability and transparency challenges in waqf management using blockchain, and Al-Daihani et al. (2023) modelled a crowdfunding cash waqf business process. None of these studies delivered a validated measurement instrument for adoption.

To conclude, there are numerous studies on banking and digital payment, but only a limited number have been published to investigate the endowment ecosystem from a blockchain perspective, and fewer still have treated the smart contract itself as a construct to be measured. To address this gap, this study adds smart contract as an exogenous construct, retains voluntariness of use as the moderator, and develops an instrument to examine the adoption intention of Malaysian public university alumni within the extended UTAUT model.

A. Smart Contract (SC)

A smart contract was first defined by Nick Szabo in 1996 as a set of promises expressed in digital form, including the protocols within which the parties perform on those promises. Unlike traditional contracts, smart contracts are self-executing programs coded on blockchain infrastructure which automatically enforce terms once pre-specified conditions are met. These contracts reduce the need for intermediaries, making transactions more efficient, transparent and tamper-resistant, qualities that align closely with the Islamic values of amanah, meaning trust, and adl, meaning justice.

Zulaikha and Rusmita (2018) present the smart contract as a transformative innovation built on blockchain technology that can directly address operational inefficiencies in traditional waqf institutions. For Islamic charitable institutions, where trust, intent and transparency are central, smart contracts offer a mechanism to execute the will of the donor precisely, reduce administrative delay and minimise the risk of mismanagement or human error. If a donor contributes a cash waqf on the condition that it fund scholarships for underprivileged students over ten years, a smart contract can be programmed to disburse a fixed amount annually and to verify recipient eligibility through integrated data checks. In this way smart contracts uphold the Islamic principle of fulfilling niyyah, meaning intent, and eliminate ambiguity or delay, which is gharar, in the execution of charitable commitments (Abdullah et al., 2022).

Al-Daihani et al. (2023) illustrate the same mechanism in the context of crowdfunded cash waqf, modelling a business process in which donations of any amount are collected through a digital platform and released to verified beneficiaries once predefined conditions are satisfied, with transaction records remaining on a shared ledger so that transparency, traceability and donor trust are preserved. Mohaiyadin et al. (2022) similarly emphasise the potential of smart contract mechanisms to automate waqf disbursement rules, standardise the issuance of digital waqf receipts, regulate the timing of fund release and enable stakeholder involvement in governance through real-time monitoring. Outside the Islamic setting, Muller (2025) applied UTAUT to smart contract adoption in supply chains and found that the perceived reliability of automated execution operates as a determinant in its own right, which lends external support to treating the contract layer as a distinct construct.

Based on the statements from the research above, it can be concluded that the smart contract is closely related to the everyday concerns that deter waqf participation, namely whether the contribution will be applied as intended and whether its application can be observed. In other words, the higher the perceived reliability of the automated enforcement, the higher the confidence of the contributor. Its perceived functionality therefore constitutes a distinct belief about the technology rather than a subset of general usefulness, which is the justification for admitting it to the model as a separate exogenous construct.

B. The Influence of Smart Contract

Based on a previous study, the UTAUT model designed by Venkatesh et al. (2003) hypothesises four variables, namely performance expectancy, effort expectancy, social influence and facilitating conditions. These variables act as predictors of behavioural intention. In this study, the author added a smart contract variable in place of one of the proposed moderators and retained voluntariness of use alone.

The smart contract variable was included because the specific technological characteristics of a waqf blockchain, in particular automated and conditional disbursement, are not fully captured by the four original constructs. When individuals perceive that smart contracts can improve transactional efficiency, reduce fraud and offer operational reliability, their behavioural intention to adopt the underlying blockchain is likely to increase. Several empirical studies have demonstrated this link. Smart contracts have been found to enhance the perception of the usefulness of blockchain and to influence intention to use directly in healthcare insurance services, and integrating smart contracts within blockchain platforms has been shown to positively affect the intention to adopt blockchain in business operations. These studies indicate that the presence and functionality of the smart contract can act as a technological enhancer, reinforcing user confidence in the broader intention to adopt a blockchain ecosystem.

Thus, the smart contract construct will be included in the UTAUT model because we discovered that automated enforcement is the dominant technical value proposition of a waqf blockchain and that it can have a major impact on contributor behaviour in the Islamic philanthropic setting. Previously it was suggested that performance expectancy, effort expectancy, social influence and facilitating conditions are all indicators of a person's behavioral intention; this study proposes that a fifth belief, concerning the contract layer itself, belongs alongside them.

C. Conceptual Framework of The Study

This study adds one exogenous construct to the standard UTAUT model, Smart Contract (SC), and retains one moderating construct, Voluntariness of Use (VoU). The constructs are defined as follows.

Performance Expectancy (PE): Performance expectancy is the degree to which an individual believes that using a system will help him or her attain gains in performance (Venkatesh et al., 2003). Alkhawaiter (2020) found that performance expectancy significantly affects behavioural intention to use digital payment instruments, and earlier work identified usefulness as the most significant determinant of consumer behavioural intention. In this study, PE refers to the extent to which alumni expect Waqfchain to improve the efficiency, convenience and traceability of their waqf contributions.

Effort Expectancy (EE): Effort expectancy is defined as the degree of ease associated with the use of the system (Venkatesh et al., 2003). It has also been described as the level of convenience associated with using a system.

Baabdullah et al. (2019) found that perceived ease of use positively influences intention to adopt mobile banking. In this study, EE refers to the extent to which alumni expect Waqfchain to be easy to learn and use.

Social Influence (SI): 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). Soomro (2019) highlighted that individuals are more inclined to use new technology systems when they perceive that their social circle encourages such usage. In this study, SI refers to the extent to which alumni perceive that peers, family, community leaders and the alumni network expect them to use Waqfchain.

Facilitating Conditions (FC): Facilitating conditions are defined as the degree to which an individual believes that an organisational and technical infrastructure exists to support use of the system (Venkatesh et al., 2003). Within a blockchain context this refers to the availability of technological resources, knowledge, infrastructure and support arrangements such as reliable internet access, technical help desks and a regulatory framework. In this study, FC refers to the extent to which alumni believe that the university and the waqf administrator will provide the technical and organisational infrastructure needed to use Waqfchain.

Smart Contract (SC): Smart contract is defined as a self-executing digital agreement whose terms are written in code and automatically enforced without human intervention, operating on a decentralised network so that once predefined conditions are met the transaction is triggered instantly and irrevocably (Zulaikha and Rusmita, 2018; Muller, 2025). In this study, SC refers to the extent to which alumni believe that automated, conditional and auditable disbursement will safeguard the integrity of their endowment.

Accordingly, the following hypotheses are advanced for the direct relationships in the model.

- H1: Performance expectancy (PE) has a positive and significant effect on the behavioural intention (BI) to use Islamic Blockchain (Waqfchain).
- H2: Effort expectancy (EE) has a positive and significant effect on the behavioural intention (BI) to use Islamic Blockchain (Waqfchain).
- H3: Social influence (SI) has a positive and significant effect on the behavioural intention (BI) to use Islamic Blockchain (Waqfchain).
- H4: Facilitating conditions (FC) have a positive and significant effect on the behavioural intention (BI) to use Islamic Blockchain (Waqfchain).
- H5: Smart contract (SC) has a positive and significant effect on the behavioural intention (BI) to use Islamic Blockchain (Waqfchain).

D. Voluntariness of Use as Moderating Variable

The UTAUT model as presented by Venkatesh et al. (2003) proposed four core variables, namely performance expectancy, effort expectancy, social influence and facilitating conditions. All four core variables presented were to be tested with moderating variables that significantly affect the core variables. According to that study, the moderating variables were age, gender, voluntariness of use and experience. This study excludes the remaining moderators and retains only voluntariness of use.

Voluntariness of use is defined as the degree to which individuals perceive their adoption of a technology as non-mandatory. It was theorised to influence the strength of the relationship between the core determinants and behavioural intention, on the reasoning that normative pressure matters more in a mandatory setting than in a discretionary one. When Venkatesh et al. (2012) extended the model into UTAUT2, voluntariness was deliberately dropped on the grounds that consumer technology use is rarely mandated by an organisation. That decision has since attracted scholarly attention, since the discretionary character of a behaviour is precisely what makes the moderator informative rather than redundant.

Waqf contribution is, by its very nature, an act of voluntary charitable giving, or *tabarru'*, that cannot be compelled by any employer or institution. The construct is therefore substantively rather than incidentally

relevant here. A meta-analysis of seventy-one studies found that environment-based voluntariness significantly moderates the effects of ease of use and usefulness on behavioural intention to use technology, and research on smart contract adoption in business organisations has highlighted the significance of voluntariness in moderating the relationship between performance expectancy and behavioural intention. When users feel they have a genuine choice in adopting the technology, their perceptions of its usefulness exert a stronger influence on their intention to use it. This study has integrated the model to place voluntariness of use as the moderating variable, as presented in Figure 1 below.

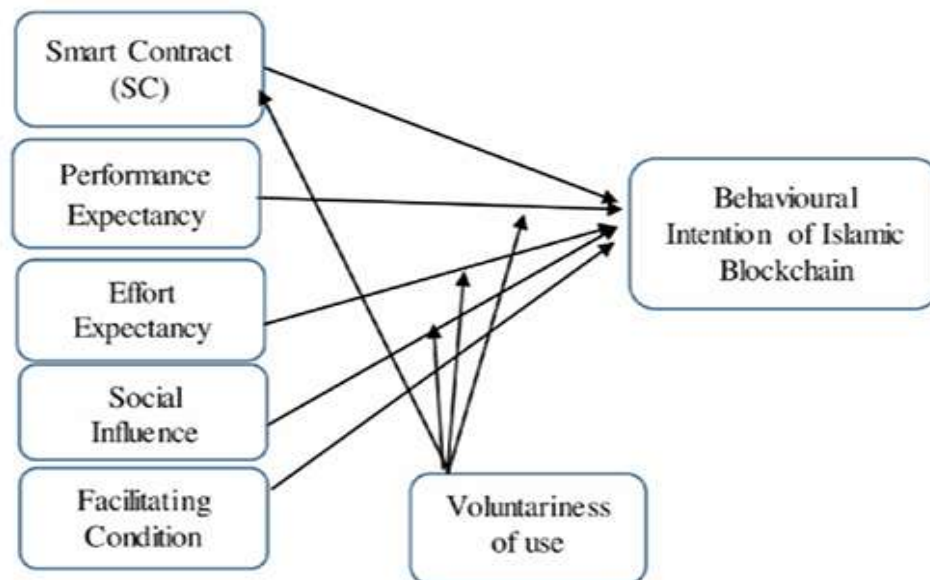


Figure 1. Conceptual framework of the Waqf Blockchain Ecosystem with voluntariness of use as a moderator

E. Voluntariness of Use

Voluntariness of use describes the extent to which an individual perceives that the decision to take up a system rests with them rather than being imposed by an employer, an institution or a social obligation that functions as compulsion. Applied to the adoption of a Waqf blockchain, the construct becomes particularly relevant because contribution is discretionary at every point. When individuals choose to engage with Waqfchain of their own decision, the impact of perceived usefulness and ease of use on their intention may be more pronounced. Similarly, the influence of recommendations from peers or community leaders could vary depending on whether adoption is perceived as voluntary or obligatory.

On the position of smart contract within this moderation structure, a distinction must be drawn. Unlike performance expectancy, effort expectancy and social influence, which are core constructs of the original UTAUT with an established body of research clarifying how moderators shape their relationship with behavioural intention, smart contract is a construct extended into this study to reflect the specific technological characteristics of a waqf blockchain and does not carry an equivalent history of empirical testing. Blockchain acceptance research remains fragmented, with existing models varying considerably in structure and findings depending on the application under study (Taherdoost, 2022; Shrestha et al., 2021). Sekaran and Bougie (2016) note that a directional hypothesis is appropriate only when there is sufficient prior research or theory to justify predicting the direction of a relationship, whereas a non-directional hypothesis is more appropriate when the relationship is acknowledged to exist but its direction cannot yet be confidently predicted. The moderating hypothesis involving smart contract is therefore stated non-directionally, while the remaining three are stated directionally.

Thus, the following moderating hypotheses are proposed in this study.

H6: Voluntariness of use significantly moderates the relationship between smart contract and behavioural intention to use Islamic Waqf Blockchain (Waqfchain).

H7: Voluntariness of use positively moderates the relationship between performance expectancy and behavioural intention to use Islamic Waqf Blockchain (Waqfchain).

H8: Voluntariness of use positively moderates the relationship between effort expectancy and behavioural intention to use Islamic Waqf Blockchain (Waqfchain).

H9: Voluntariness of use positively moderates the relationship between social influence and behavioural intention to use Islamic Waqf Blockchain (Waqfchain).

The literature reviewed above indicates that the discretionary character of adoption conditions the strength with which beliefs about a technology translate into intention, and that this conditioning is especially pronounced where the behaviour in question is itself an act of free choice. This study accordingly proposes a framework in which five exogenous constructs, namely performance expectancy, effort expectancy, social influence, facilitating conditions and smart contract, predict behavioural intention to use Waqfchain, with voluntariness of use moderating four of those five paths.

UTAUT was selected because it consolidates eight earlier acceptance models and has consistently shown stronger explanatory power than its predecessors (Venkatesh et al., 2003), and recent extensions to blockchain settings indicate that it continues to explain more than half of the variance in intention to adopt emerging technologies. While many studies have used the technology acceptance model, very few have applied UTAUT in an Islamic endowment setting. This study therefore extends UTAUT by adding smart contract as an exogenous construct in order to examine adoption of the proposed waqf blockchain among Malaysian public university alumni.

Before that framework can be tested, however, the instrument that operationalises it must be screened. The remainder of this article is devoted to that task.

MATERIALS AND METHODOLOGY

This study is divided into four stages: pretest, development test, validating test and hypothesis testing. The first phase, the pretest, includes developing and refining the questionnaire items, followed by expert, face and content validity procedures. The second phase, the pilot study, focuses on establishing the scale. In this step, responses were collected from millennial alumni of Malaysian public universities who reside in the urban central region, by utilising the questionnaire items developed in the first phase, and the scale was defined using exploratory factor analysis (EFA). In the third step, confirmatory factor analysis (CFA) is used to validate the measurement scale that was previously defined, on an independent field sample drawn from the same population but from different respondents. The fourth step tests the hypothesised structural relationships. This article reports the first two stages.

The sample size for the pilot study was established using the minimum sampling requirement for pilot studies. Memon et al. (2020) note that a pilot study demands a smaller sample size than an actual study, and a minimum of 100 respondents is recommended where the researcher intends to perform exploratory factor analysis to assess the underlying factor structure (Muda et al., 2018). In this study, 150 questionnaires were distributed to a sub-sample of the target population to ensure the minimum was achieved. Data collection yielded 106 responses. Primary data were collected through an online questionnaire distributed across alumni groups of major public institutions in the central region, and a random sampling technique was used.

Most researchers believe pretesting is essential before collecting responses to a questionnaire, particularly where the questions used are adapted from another study, since several problems with items can only be found by pretesting them. The author summarised the purpose of the pretesting process as establishing whether: 1. Respondents comprehend all the terms and concepts in the questionnaire. 2. Closed questions include at least one response option for all respondents. 3. All respondents read the questions in the same way. 4. Correct answer selections can be chosen. 5. Every survey question is designed to measure what it is supposed to measure. 6. The questionnaire makes a good first impression and so encourages people to respond. 7. Finally, whether any questionnaire component reveals the bias of the researcher.

In this study, all items were included in the pretest after the content validity, face validity and translation procedures. The language of the questionnaire must be straightforward. The instructions and explanations provided for each section and item must be clear and concise.

The theoretical foundation of the scale provided in this study rests on the fundamental principles of Islamic muamalat as applied to endowment, namely the perpetuity of the corpus, the binding character of donor intent, or niyyah, the obligation of trusteeship, or amanah, and the avoidance of uncertainty, or gharar, in the execution of the waqf or endowment. Understanding these concepts is critical for Malaysian providers of blockchain-based waqf platforms.

According to Balbinotti et al. (2007), the content validity evaluation sheet must encompass three criteria in order to make the instrument as clear as possible. The three criteria are as follows:

- 1) Clarity of language: Examines the phrasing of the questionnaire in the context of the target audience. Accordingly, the panellists were asked, "Do you believe the questions are straightforward and understandable?"
- 2) Practical pertinence: Assesses the relevance of the question to the day-to-day activities of the typical user. The panellists were asked, "Do you believe this item is relevant to this population, and to what extent?"
- 3) Theoretical dimension: Assesses the relevance of the question to one of the construct categories covered by the questionnaire. The panellists were asked, "To which theoretical dimension does this question belong? Please only check the box next to the option that best describes the item."

On the items that were initially generated, altered and customised for the study, the experts were asked to rate each item for relevance to its construct on a four-point scale: 1 = not relevant, 2 = somewhat relevant, 3 = quite relevant, 4 = highly relevant. The instrument itself uses a ten-point interval scale. While business research predominantly employs five-point or seven-point Likert scales, there is a growing trend towards the ten-point scale in order to augment the precision and granularity of respondent data. Dawes (2008) established that ten-point scales yield enhanced variance results relative to five-point or seven-point scales, since they afford respondents a wider range in which to articulate nuanced positions, and Awang (2015) endorses the ten-point scale for studies employing structural equation modelling on the grounds that it produces superior outcomes in confirmatory factor analysis and in assessments of discriminant validity. Consequently, this study adopts a ten-point interval scale for all latent constructs.

The pilot study consists of preliminary data screening, exploratory factor analysis and reliability analysis.

A. Preliminary Analysis of the Pilot Data

1. *Assessment of outliers*

The initial pilot dataset comprised 106 participants who completed the instrument measuring seven theoretical constructs: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Smart Contract (SC), Voluntariness of Use (VoU) and Behavioural Intention (BI). Data screening is a fundamental preliminary procedure in quantitative research, since extreme values can affect parameter estimation, amplify error variance and breach the assumptions that underpin parametric methods. Analysis of the standard deviation for each individual respondent confirmed that there were no unengaged responses, as all variances exceeded one.

Univariate outlier detection was performed using standardised z-scores for all assessed variables. Following Tabachnick and Fidell (2019), a criterion of ± 3.29 was used to locate univariate outliers, a benchmark that approximates the 99.9th percentile of the standard normal distribution. Application of this criterion identified and removed 19 cases from the starting pool of 106, reducing the dataset to 87. A multivariate screen was then conducted using the Mahalanobis distance, with cases exceeding the critical chi-square threshold at $p < .001$ classified as potential multivariate outliers. This assessment indicated the absence of any additional multivariate outliers beyond those already eliminated. The final usable sample for all subsequent analyses therefore comprised $N = 87$ participants, of whom 28.3 per cent were aged 25 to 29, 36.8 per cent aged 30 to 34 and 34.9

per cent aged 35 to 40 at the point of response.

2. Normality test

The evaluation of univariate normality is an essential prerequisite for factor analysis, since significant deviations can distort factor extraction, bias parameter estimates and elevate error rates. Formal statistical tests of normality are highly sensitive to sample size and frequently reject the null hypothesis even where deviations are minimal, so the present study employed descriptive indices of distributional shape, namely skewness and kurtosis. Hair et al. (2019) contend that skewness and kurtosis values as high as ± 3 and ± 10 respectively may not exert a significant influence on analytical outcomes, and Kline (2016) adopts the same thresholds. The results are presented in Table 1.

Table 1. Descriptive statistics and normality assessment for construct means (N = 87)

Construct	Min.	Max.	Mean	Std. Dev.	Skewness	Kurtosis	Result
Performance Expectancy	6.22	10	8.3742	0.6419	0.254	1.883	Normal
Effort Expectancy	5.56	10	8.1992	0.8137	-0.672	1.629	Normal
Social Influence	4.25	10	8.171	0.91977	-1.298	4.552	Normal
Facilitating Conditions	6.25	10	8.3951	0.69932	0.279	1.264	Normal
Smart Contract	5.7	10	8.3322	0.72969	-0.039	1.617	Normal
Voluntariness of Use	6.2	10	8.3253	0.76815	-0.078	0.707	Normal
Behavioural Intention	5.78	10	8.2937	0.79926	-0.088	1.371	Normal

Note: Std. Error of skewness = .258; Std. Error of kurtosis = .511. Acceptance thresholds ± 3 (skewness) and ± 10 (kurtosis).

Source: Prepared by the authors (2026)

All constructs exhibited skewness values within the acceptable range of ± 3 , the largest being Social Influence at -1.298. Kurtosis values were similarly within acceptable bounds, with Social Influence again showing the highest value at 4.552, suggesting a somewhat leptokurtic distribution with heavier tails than the normal. Overall, these construct-level distributional properties indicate that the data satisfied the normality requirement and were suitable for subsequent parametric analyses, including exploratory factor analysis and correlation-based multicollinearity diagnostics.

3. Multicollinearity test

Multicollinearity involves the presence of notable correlations among predictor variables within a regression context or among components in a factor analysis. Marked multicollinearity can yield unreliable parameter estimates, inflated standard errors and difficulty in distinguishing the specific contribution of individual predictors. Evaluation was conducted using two complementary methods: inspection of the Pearson correlation matrix among construct means, reported in Table 2, and computation of variance inflation factors and tolerance statistics within a multiple regression model predicting Behavioural Intention from the six predictor constructs, reported in Table 3.

Table 2. Pearson correlation matrix among construct means (N = 87)

	PE	EE	SI	FC	SC	VoU	BI
PE	1	.580**	.551**	.648**	.628**	.761**	.737**
EE	.580**	1	.894**	.727**	.809**	.716**	.743**
SI	.551**	.894**	1	.745**	.788**	.701**	.762**
FC	.648**	.727**	.745**	1	.786**	.729**	.707**
SC	.628**	.809**	.788**	.786**	1	.763**	.809**

VoU	.761**	.716**	.701**	.729**	.763**	1	.872**
BI	.737**	.743**	.762**	.707**	.809**	.872**	1

** Correlation is significant at the 0.01 level (2-tailed).

Source: Prepared by the authors (2026)

All pairwise correlations among the seven construct means achieved statistical significance at $p < .01$, indicating a considerable degree of shared variance. Coefficients ranged from a minimum of $r = .551$ between PE and SI to a maximum of $r = .894$ between EE and SI. Four correlations exceeded the frequently cited practical warning threshold of $r = .80$, namely EE–SI at .894, EE–SC at .809, SC–BI at .809 and VoU–BI at .872. The high correlation between Effort Expectancy and Social Influence implies that these two constructs share approximately 80% of their variance, raising a question regarding their discriminant validity; the same concern applies to Voluntariness of Use and Behavioural Intention. These pairs are examined further in Section IV.I. Theoretically the relationship is coherent, since during the initial phases of technology adoption users frequently depend on social indicators to judge how manageable a technology appears; where a peer network signals that a system is easy to use, the social impetus to adopt it is amplified.

Table 3. Collinearity statistics for the six predictor constructs

Predictor	Std. Beta	t	Sig.	Tolerance	VIF (< 10)
Performance Expectancy	0.163	2.277	0.025	0.399	2.506
Effort Expectancy	-0.095	-0.866	0.389	0.169	5.914
Social Influence	0.278	2.581	0.012	0.178	5.634
Facilitating Conditions	-0.116	-1.409	0.163	0.305	3.279
Smart Contract	0.28	3.007	0.004	0.237	4.219
Voluntariness of Use	0.493	5.617	0	0.267	3.75

Dependent variable: Mean_BI.

Source: Prepared by the authors (2026)

Commonly cited thresholds suggest that VIF values exceeding 5 warrant attention and values exceeding 10 indicate severe multicollinearity, while tolerance below .20 is problematic. Two predictors, Effort Expectancy at $VIF = 5.914$ and Social Influence at $VIF = 5.634$, exhibited values slightly above 5, but all values remained well below the critical threshold of 10, indicating that multicollinearity, while present, does not severely compromise the estimates. The data were therefore concluded suitable to proceed to exploratory factor analysis.

B. Exploratory Factor Analysis

Exploratory factor analysis constitutes a methodological process aimed at elucidating the latent structure among the variables under investigation. The application of factor analysis is predicated upon the principles of data summarisation and reduction. According to Williams, Onsmann and Brown (2010), there are eight EFA objectives, which are as follows: 1) To reduce the number of variables. 2) Investigate the structure or interrelation of variables. 3) Detection and assessment of the unidimensionality of a theoretical construct. 4) Assess the construct validity of a scale, test or instrument. 5) Creation of simple, or parsimonious, analysis and interpretation. 6) Address multicollinearity, that is two or more linked variables. 7) Used in the development of theoretical constructions. 8) Used to support or refute presented theories.

Taherdoost, Sahibuddin and Jalaliyoon (2014) note that factor analysis divides into two main categories. EFA allows the researcher to explore the main variables in order to create a theory or model from a relatively large set of dimensions, whereas confirmatory factor analysis is applied to test a proposed theory or model as a form of structural equation modelling. EFA was therefore performed on the pilot dataset in this study to determine the underlying factor structure of the constructs and to observe how Millennial alumni of public universities responded to the pilot questionnaire.

The procedure followed the five-stage process set out by Hair et al. (2019). Stage 1 defines the objectives of the analysis, namely data summarisation, data reduction and the identification of underlying variable structures. Stage 2 designs the factor analysis to reveal a factor structure consistent with the theoretical constructs of the study. Stage 3 verifies that the underlying assumptions are satisfied, including normality, absence of excessive multicollinearity and sampling adequacy. Stage 4 derives the factors and assesses model fit through principal component analysis as the extraction method, followed where more than one component emerges by varimax rotation with Kaiser normalisation. Stage 5 interprets the derived factors against the decision criteria, namely retention of items with a significant factor loading, a satisfactory total variance explained and retention only of factors with an eigenvalue greater than one, consistent with the Kaiser criterion.

A note on the extraction method is warranted, because principal component analysis (PCA) and common-factor methods such as principal axis factoring (PAF) rest on different assumptions. PCA analyses the total variance of the items and yields components that are linear composites of them, whereas common-factor methods analyse only the variance the items share and treat unique variance as error; strictly, only common-factor methods estimate latent constructs (Fabrigar et al., 1999; Costello and Osborne, 2005). PCA was retained at this stage for three reasons. First, the purpose of the pilot analysis was item screening and data reduction, that is, deciding which items to carry forward, rather than estimating the parameters of latent constructs, a task deferred to confirmatory factor analysis. Second, PCA and common-factor solutions converge when communalities are moderate to high and each factor is defined by several items (Velicer and Jackson, 1990); in the final solutions each construct retained six to nine items and every retained loading was .634 or above. Third, PCA is the extraction method most commonly used in the instrument-development studies on which this procedure is modelled (Williams et al., 2010), which preserves comparability. Accordingly, the procedure is described throughout as exploratory factor analysis using principal component extraction, and the resulting loadings are treated as screening evidence rather than as latent-construct estimates. Because PCA loadings tend to be somewhat higher than common-factor loadings, a principal axis factoring solution should be examined on the field sample as a sensitivity check.

EFA was conducted separately for each construct rather than on the pooled item set. With 87 usable cases and 63 initial items, a pooled analysis would have a case-to-item ratio below 1.5:1, well short of the minimum of five cases per variable recommended by Hair et al. (2019), and would produce unstable loadings. Construct-level analysis establishes the dimensionality of each scale, but it cannot show whether items discriminate between constructs. Evidence on that question is examined in Section IV.I and must ultimately be established in the confirmatory stage.

Communalities and factor loadings were examined in each case, communalities representing the proportion of variance in each item that can be explained by the extracted factor and factor loading expressing the association of each item with the underlying factor. An item exhibiting a communality below .50 was considered for exclusion, and any item yielding a low loading or demonstrating cross-loading was likewise discarded. The exploratory factor analysis was carried out in three stages: the sampling adequacy test, the factor extraction test and the component matrix test, followed by a reliability test.

1. Sampling adequacy test

Hair et al. (2019) and Field (2009) state that the KMO statistic in the table labelled KMO and Bartlett's Test should be greater than 0.5 as a bare minimum, as can be seen in Table 4. If it falls below 0.5, the researcher needs to collect more data, meaning that the data gathered for the EFA were insufficient. Kaiser (1974) proposed the following interpretive guidelines: values below .50 are unacceptable, values between .50 and .60 are miserable, values between .60 and .70 are mediocre, values between .70 and .80 are middling, values between .80 and .90 are meritorious, and values above .90 are marvellous. Both sources also state that Bartlett's test of sphericity should be significant, with a significance level less than .05.

Table 4. KMO and Bartlett's test for the final construct solutions

No.	Constructs	KMO (> 0.50)	Bartlett's Approx. Chi-Square	df	Sig.	Interpretation
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1	Performance Expectancy	0.857	142.134	15	0	Meritorious
2	Effort Expectancy	0.847	341.415	36	0	Meritorious
3	Social Influence	0.855	330.536	28	0	Meritorious
4	Facilitating Conditions	0.849	142.103	15	0	Meritorious
5	Smart Contract	0.867	305.268	28	0	Meritorious
6	Voluntariness of Use	0.776	247.464	21	0	Middling
7	Behavioural Intention	0.875	412.259	36	0	Meritorious

Source: Prepared by the authors (2026)

All seven constructs were therefore suitable for factor analysis.

2. Factor extraction test

The factor extraction test determines the number of dimensions or components that comprise the concept and the variation explained by each dimension. The outcomes in Table 5 show that six of the seven constructs resolved into a single component on the computed eigenvalue criterion of more than 1.0, while Voluntariness of Use extracted two components. The eigenvalues of the first components are 3.123, 4.705, 4.496, 3.115, 4.411, 3.653 and 5.202 for PE, EE, SI, FC, SC, VoU and BI respectively, with a second component of 1.081 for VoU. The total variance for estimating each construct falls between 51.922 per cent and 67.631 per cent. The total variance explained is acceptable since every construct surpassed the 50 per cent minimum for a unidimensional scale, with Social Influence, Smart Contract, Behavioural Intention and Voluntariness of Use approaching or exceeding the 60 per cent benchmark often cited as preferable for a high-quality instrument.

Table 5. Total variance explained for the final construct solutions

Construct	Component	Eigenvalue	% of Variance	Cumulative %	Items Retained
Performance Expectancy	1	3.123	52.042	52.042	6 of 9
Effort Expectancy	1	4.705	52.278	52.278	9 of 9
Social Influence	1	4.496	56.197	56.197	8 of 8
Facilitating Conditions	1	3.115	51.922	51.922	6 of 8
Smart Contract	1	4.411	55.136	55.136	9 of 10
Voluntariness of Use	1	3.653	52.184	52.184	7 of 10
	2	1.081	15.447	67.631	
Behavioural Intention	1	5.202	57.795	57.795	9 of 9

Extraction Method: Principal Component Analysis.

Source: Prepared by the authors (2026)

3. Component matrix test

Table 6 shows the components extracted from EFA and their respective items. The factor loading for every item is expected to exceed .50 in order to be retained for practical significance, with .40 treated as the lower tolerance for a moderate loading. Six items were finally retained to measure Performance Expectancy, nine for Effort Expectancy, eight for Social Influence, six for Facilitating Conditions, nine for Smart Contract, seven for Voluntariness of Use across two components and nine for Behavioural Intention. The components will then be modelled and analysed in confirmatory factor analysis using AMOS.

Table 6. Component matrix extracted

PE	Load.	EE	Load.	SI	Load.	FC	Load.
PE1	0.788	EE2	0.811	SI1	0.827	FC3	0.783
PE2	0.74	EE1	0.753	SI4	0.811	FC1	0.75
PE8	0.716	EE3	0.752	SI8	0.79	FC6	0.73
PE5	0.706	EE6	0.738	SI2	0.787	FC2	0.706
PE6	0.705	EE5	0.725	SI3	0.775	FC5	0.687
PE9	0.669	EE8	0.695	SI5	0.706	FC4	0.661
		EE9	0.693	SI6	0.639		
		EE7	0.668	SI7	0.634		
		EE4	0.658				

SC	Load.	VoU	Comp. 1	Comp. 2	BI	Load.
SC5	0.808	VOU6	0.884	0.144	BI9	0.816
SC8	0.754	VOU2	0.777	0.175	BI1	0.806
SC2	0.743	VOU1	0.746	0.323	BI4	0.786
SC4	0.74	VOU8	0.699	0.335	BI7	0.762
SC1	0.732	VOU3	0.21	0.868	BI6	0.751
SC7	0.727	VOU5	0.238	0.786	BI2	0.747
SC3	0.719	VOU7	0.224	0.718	BI5	0.734
SC6	0.712				BI3	0.732
SC10	0.699				BI8	0.702

Extraction Method: Principal Component Analysis. Rotation Method for Voluntariness of Use: Varimax with Kaiser Normalization; rotation converged in 3 iterations. Single-component solutions are unrotated.

Source: Prepared by the authors (2026)

4. Reliability Test

According to Sekaran (2003), the degree to which a measure is free of bias, and thus ensures consistent measurement over time and across the various items of the instrument, is determined by its reliability. In other words, the reliability of a measure is an indicator of the stability and consistency of the instrument in measuring a concept, and it facilitates determining the goodness of a measure. Cronbach's coefficient alpha is the most widely used measure of inter-item consistency for multipoint-scaled items. Alpha values of .70 or above are generally considered acceptable for research purposes, values of .80 or above good, and values of .90 or above excellent, although excessively high values above .95 may indicate item redundancy rather than superior reliability. The results are reported in Table 7.

Table 7. Reliability Results

Construct	No. of items	Cronbach's Alpha	Acceptability	Threshold
Performance Expectancy	6	0.815	Good	> .80
Effort Expectancy	9	0.885	Good	> .80
Social Influence	8	0.888	Good	> .80



Facilitating Conditions	6	0.812	Good	> .80
Smart Contract	9	0.891	Good	> .80
Voluntariness of Use	7	0.846	Good	> .80
Behavioural Intention	9	0.908	Excellent	> .90
Total	54	—	—	—

Thresholds after Nunnally and Bernstein (1994) and George and Mallery (2003).

Source: Prepared by the authors (2026)

Thus, according to Table 7 above, all constructs of Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Smart Contract, Voluntariness of Use and Behavioural Intention show an alpha value between 0.812 and 0.908, which means the internal consistency of the constructs is good to excellent. Nunnally first proposed in 1967 that the minimum acceptable Cronbach alpha for preliminary research be in the range of 0.5 to 0.6, but in the 1978 edition of Psychometric Theory he revised the recommendation upward to 0.7. Every construct in this study comfortably exceeds that revised level.

5. Stage three: Validation test

Confirmatory factor analysis is a statistical method for confirming the factor structure of a set of observed data. CFA examines the unidimensionality, validity and reliability of a construct. Researchers use the CFA approach to validate the measurement model by analysing the value of each item in measuring its construct; items with a low factor loading of less than 0.6 indicate that the item is not contributing to the measurement of the construct and must be eliminated from the measurement model. However, the deletion of items in CFA cannot exceed twenty per cent of the initial item count in the construct, since above that level the construct fails to achieve validity.

The confirmatory stage must satisfy four requirements before the instrument is used for structural hypothesis testing. First, unidimensionality: each retained item should load at 0.6 or above on its intended construct. Second, measurement-model fit, reported with at least one index from each family: a normed chi-square (χ^2/df) below 3.0, CFI and TLI at or above .90 and preferably .95, and RMSEA and SRMR at or below .08 (Hu and Bentler, 1999; Hair et al., 2019). Third, convergent validity and reliability: average variance extracted of at least .50 and composite reliability of at least .70. Fourth, discriminant validity, assessed by both the Fornell–Larcker criterion (Fornell and Larcker, 1981) and the heterotrait–monotrait ratio, with HTMT values below .85 for conceptually distinct constructs and below .90 at most (Henseler et al., 2015). Given the pilot evidence in Section IV.I, the Effort Expectancy–Social Influence and Voluntariness of Use–Behavioural Intention pairs require specific attention, including a chi-square difference test comparing each two-factor specification with a model in which the pair is constrained to correlate at unity. The dimensional structure of Voluntariness of Use must likewise be tested rather than assumed (Section IV.F). Only when these conditions are met should the five direct and four moderating hypotheses be tested.

RESULTS AND DISCUSSION

Because seven constructs were screened independently, exploratory factor analysis was performed separately for each measurement scale. Each subsection below reports the initial solution, the diagnostic basis for any item removal, and the final retained structure.

A. Exploratory Factor Analysis for Performance Expectancy

The initial EFA for Performance Expectancy included nine items. The KMO value was .874, indicating meritorious sampling adequacy, and Bartlett's test was statistically significant at $p < .001$, confirming the factorability of the correlation matrix. Principal component analysis with varimax rotation extracted two components with eigenvalues greater than 1.0, accounting for 54.424 per cent of the total variance explained.

Examination of the rotated component matrix, however, revealed that item PE3 cross-loaded heavily on Component 2 with a loading of .927, while items PE4 and PE7 exhibited low loadings on both components at

.502 and .516 respectively on Component 1. Cross-loading occurs when an item loads substantially on more than one factor, indicating that the item measures multiple underlying constructs and thus lacks discriminant validity. Items with low loadings fail to share sufficient common variance with the underlying factor and should be considered for removal. Following the recommendations of Hair et al. (2019) and Tabachnick and Fidell (2019), items PE3, PE4 and PE7 were removed and the EFA re-run with the remaining six items.

The revised EFA yielded a single-component solution with a KMO value of .857, again meritorious, and a statistically significant Bartlett's test at $p < .001$. The single component accounted for 52.042 per cent of the total variance, exceeding the commonly cited minimum of fifty per cent for a unidimensional scale. The scree plot displayed the expected downward slope and broke at the second component before descending into an almost horizontal line. The six retained items exhibited the following loadings: PE1 = .788, PE2 = .740, PE5 = .706, PE6 = .705, PE8 = .716 and PE9 = .669. All loadings exceeded the .50 threshold for practical significance. These results indicate that the six-item Performance Expectancy scale exhibits a clear unidimensional structure with strong item-factor relationships.

A possible reading of the three deleted items is offered tentatively, since item content was not the basis for their removal. PE3 and PE4 were phrased in terms of productivity and overall performance, language carried over from workplace applications of UTAUT, and may transfer less cleanly to a voluntary donor context. PE7, which concerned the transparency of fund allocation, may overlap conceptually with the Smart Contract construct. Whether the six retained items capture performance expectancy as a contributor experiences it is a question for the confirmatory stage and, ultimately, for data collected after deployment.

B. Exploratory Factor Analysis for Effort Expectancy

The EFA for Effort Expectancy included all nine original items. The KMO value was .847 and Bartlett's test was statistically significant at $p < .001$, confirming data suitability for factor analysis. A single component was extracted, accounting for 52.278 per cent of the total variance. The scree plot exhibited the downward-sloping shape and broke at the second component before descending into an almost horizontal line.

All nine items were retained, exhibiting the following loadings: EE1 = .753, EE2 = .811, EE3 = .752, EE4 = .658, EE5 = .725, EE6 = .738, EE7 = .668, EE8 = .695 and EE9 = .693. All loadings exceeded the .50 threshold for practical significance. The unidimensional structure and consistently strong loadings provide evidence that the nine-item Effort Expectancy scale measures a single coherent construct, and no item reduction was required. Because respondents were rating a platform they had not yet used, the result shows that anticipated ease of use formed a single dimension in the pilot data; it does not by itself indicate how ease of use would be experienced in practice.

C. Exploratory Factor Analysis for Social Influence

The EFA for Social Influence included eight items. The KMO value was .855 and Bartlett's test was statistically significant at $p < .001$. A single component was extracted, accounting for 56.197 per cent of the total variance, which exceeds the fifty per cent minimum and approaches the sixty per cent benchmark often cited as preferable for high-quality instruments. The scree plot broke at the second component before flattening.

All eight items were retained, with the following loadings: SI1 = .827, SI2 = .787, SI3 = .775, SI4 = .811, SI5 = .706, SI6 = .639, SI7 = .634 and SI8 = .790. All loadings exceeded the .50 threshold for practical significance. The Social Influence scale thus exhibits a clear unidimensional structure with strong item-factor relationships, and no reduction was required. The two lowest loadings, SI6 and SI7, remain comfortably above the threshold. A clean within-construct solution does not, however, address the high correlation between Social Influence and Effort Expectancy observed at the preliminary stage, which is examined in Section IV.I.

D. Exploratory Factor Analysis for Facilitating Conditions

The initial EFA for Facilitating Conditions included eight items. The KMO value was .824 and Bartlett's test was statistically significant at $p < .001$. A single component was extracted, accounting for 47.646 per cent of the total variance, which falls below the fifty per cent minimum.

Examination of the communalities, which represent the proportion of the variance of each item explained by the extracted factor, revealed that items FC7 with a communality of .403 and FC8 with a communality of .400 fell below the recommended threshold of .50. Communalities below .50 indicate that less than half of the variance of an item is shared with the underlying factor, suggesting that the item is a poor indicator of the construct. Consequently, items FC7 and FC8 were removed and the EFA re-run with the remaining six items.

The revised EFA yielded a single-component solution with a KMO value of .849, meritorious, and a statistically significant Bartlett's test at $p < .001$. The single component accounted for 51.922 per cent of the

total variance, representing a substantial improvement over the initial 47.646 per cent and exceeding the fifty per cent minimum threshold. The six retained items exhibited the following loadings: FC1 = .750, FC2 = .706, FC3 = .783, FC4 = .661, FC5 = .687 and FC6 = .730. All loadings exceeded the .50 threshold for practical significance. The removal of the two low-communality items thus resulted in a more parsimonious and psychometrically sound Facilitating Conditions scale.

E. Exploratory Factor Analysis for Smart Contract

The preliminary EFA conducted for the construct of Smart Contract comprised ten items designed to measure the perceived reliability, automation and auditability of the contract layer. The Kaiser-Meyer-Olkin measure of sampling adequacy yielded a value of .889, which is meritorious, and Bartlett's test of sphericity returned a statistically significant result at $p < .001$, affirming the suitability of the data for factor analysis.

A single component was extracted, accounting for 51.434 per cent of the overall variance. Detailed examination of the communalities revealed that item SC9 possessed a notably low communality of .350 together with a factor loading of .592, below the .60 criterion applied to this construct, prompting concern regarding its contribution to the model. Item SC9 was accordingly removed and the analysis re-run, and the final solution retained nine items.

The conclusive EFA results for Smart Contract yielded a single-component solution with a KMO value of .867, again meritorious, and a statistically significant Bartlett's test at $p < .001$. This single component accounted for 55.136 per cent of the total variance, a marked improvement over the initial 51.434 per cent and comfortably above the fifty per cent minimum. The nine retained items exhibited the following loadings: SC1 = .732, SC2 = .743, SC3 = .719, SC4 = .740, SC5 = .808, SC6 = .712, SC7 = .727, SC10 = .699 and SC8 = .754. All loadings surpassed the .50 threshold for practical significance, suggesting robust relationships between the items and the underlying factor.

This result is consistent with the argument for admitting Smart Contract as an extension of UTAUT, since its nine items formed a single coherent component with a narrow loading range from .699 to .808. It is not sufficient, however, to establish that the construct is empirically separable from the original UTAUT constructs. Its attenuation-corrected correlations with Facilitating Conditions and Effort Expectancy are high (Section IV.I), and its distinctiveness must be demonstrated in the confirmatory stage.

F. Exploratory Factor Analysis for Voluntariness of Use

The EFA for Voluntariness of Use proved the most complex of the seven, requiring multiple iterations to achieve a satisfactory solution. The initial EFA included ten items and yielded a KMO value of .855 and a statistically significant Bartlett's test at $p < .001$. However, two components were extracted, accounting for 59.824 per cent of the total variance, which suggested that the construct as originally operationalised was not unidimensional. Items VOU9 and VOU10 were removed on account of loadings below .60, VOU9 loading at .491 on Component 1 and .436 on Component 2 and VOU10 at .573 and .412 respectively.

The EFA was re-run with the remaining eight items, but two components were still extracted. Further examination revealed that item VOU4 exhibited a cross-loading problem, loading at .391 on Component 1 and .585 on Component 2 and thus lacking discriminant validity. Item VOU4 was therefore removed and the EFA re-run with seven items.

The final EFA for Voluntariness of Use yielded a two-component solution with a KMO value of .776, which is

middling, and a statistically significant Bartlett's test at $p < .001$. The two components accounted for 67.631 per cent of the total variance, which substantially exceeds the fifty per cent minimum threshold and surpasses the sixty per cent benchmark for high-quality instruments. The seven retained items loaded on two distinct components. Component 1 comprised VOU6 at .884, VOU2 at .777, VOU1 at .746 and VOU8 at .699; Component 2 comprised VOU3 at .868, VOU5 at .786 and VOU7 at .718. All loadings exceeded the .60 threshold, indicating strong item-factor relationships.

The two-component structure requires theoretical interpretation rather than automatic acceptance, and inspection of item content suggests a substantive distinction. Component 2 comprises VOU3 ("I expect to have the freedom to choose whether or not to use Waqf Blockchain"), VOU5 ("I expect that there will be no pressure from my organization or peers to use Waqf Blockchain") and VOU7 ("Using Waqf Blockchain will be my personal decision"). These items describe perceived freedom from compulsion, which corresponds closely to voluntariness as originally defined by Moore and Benbasat (1991) and adopted by Venkatesh et al. (2003). Component 1 is anchored by VOU6 ("I would still use Waqf Blockchain even if it weren't promoted by others") and VOU8 ("I would be interested in trying Waqf Blockchain even if its use is optional"), together with VOU1 and VOU2. VOU6 and VOU8 in particular express a willingness to use the platform in the absence of external prompting, which may be termed autonomous willingness.

This distinction has two consequences. First, Component 1 partly overlaps in content with behavioural intention, since a stated willingness to use is close to an intention to use. This offers a plausible explanation for the very high correlation between Voluntariness of Use and Behavioural Intention ($r = .872$), and it raises a concern for the moderation hypotheses, because a moderator that shares content with the outcome it conditions can produce ambiguous interaction effects. Second, the two components need not form a single higher-order construct. The confirmatory stage should therefore compare three specifications: a single first-order factor, two correlated first-order factors, and a second-order factor with two first-order dimensions. The second-order form should be retained only if it is supported by model fit, by substantial loadings of the first-order factors on the higher-order factor, and by discriminant validity against Behavioural Intention. If Component 1 cannot be distinguished from Behavioural Intention, the more defensible course is to operationalise the moderator using the perceived-freedom items alone, since these represent the construct as originally theorised.

G. Exploratory Factor Analysis for Behavioural Intention

The exploratory factor analysis conducted for Behavioural Intention comprised nine measurement items. The KMO value obtained was .875, indicating a meritorious level of sampling adequacy, complemented by Bartlett's test of sphericity which yielded a statistically significant result at $p < .001$, thereby affirming the appropriateness of the factor analysis.

A single component was extracted, accounting for 57.795 per cent of the overall variance, a proportion that not only surpasses the fifty per cent minimum but also approaches the more stringent sixty per cent benchmark typically associated with high-quality measurement instruments. The scree plot exhibited the expected downward slope and broke at the second component before descending into an almost horizontal line.

All nine items were retained in the final model, with the following loadings: BI1 = .806, BI2 = .747, BI3 = .732, BI4 = .786, BI5 = .734, BI6 = .751, BI7 = .762, BI8 = .702 and BI9 = .816. Every loading significantly exceeded the .50 threshold for practical significance, demonstrating robust relationships between the items and the underlying factor. Consequently, the Behavioural Intention scale is characterised by a distinct unidimensional structure underpinned by strong psychometric properties, reinforcing its validity as the endogenous measure in this study.

H. Reliability Analysis of the Retained Scales

Internal consistency reliability was assessed for each of the seven constructs using Cronbach's alpha coefficient, which quantifies the extent to which items within a scale are intercorrelated and thus measure a common underlying construct. The coefficients were as follows: Performance Expectancy at .815, Effort Expectancy at .885, Social Influence at .888, Facilitating Conditions at .812, Smart Contract at .891, Voluntariness of Use at .846 and Behavioural Intention at .908. All seven constructs exhibited alpha values exceeding the .80 threshold

for good internal consistency, with Behavioural Intention exceeding the .90 threshold for excellent internal consistency. No construct approached the .95 level at which redundancy becomes a concern.

These results provide strong evidence that the items within each scale are highly intercorrelated and measure coherent underlying constructs. The reliability coefficients also suggest that the item-reduction procedures implemented during exploratory factor analysis, specifically the removal of items with low loadings, low communalities or cross-loading problems, successfully enhanced the internal consistency of the scales by eliminating items that contributed measurement error rather than true-score variance.

It is noteworthy that the Behavioural Intention scale exhibited the highest alpha coefficient at .908. This finding is consistent with the EFA results, which showed that all nine Behavioural Intention items loaded strongly on a single component, with loadings ranging from .702 to .816, and that the component accounted for 57.795 per cent of the total variance. The convergence of evidence from EFA, indicating a strong unidimensional structure, and from reliability analysis, indicating excellent internal consistency, provides robust support for the psychometric quality of the scale. Similarly, Smart Contract at .891, Social Influence at .888 and Effort Expectancy at .885 all exhibited strong internal consistency, corroborating the EFA findings of clean unidimensional structures for these constructs.

Performance Expectancy at .815 and Facilitating Conditions at .812 exhibited good internal consistency, while Voluntariness of Use at .846 fell between the two groups. The slightly lower values for Performance Expectancy and Facilitating Conditions may reflect the fact that both scales were reduced to six items following item removal during EFA, whereas the scales with higher values retained eight or nine items after screening. Since alpha is sensitive to scale length, a reduction of that magnitude will depress the coefficient even where the retained items are sound. All values nonetheless exceeded the .80 threshold, indicating that all seven scales are sufficiently reliable for use in subsequent confirmatory analysis and hypothesis testing. Internal consistency, however, concerns items within a scale and says nothing about whether scales are distinct from one another, which is the question addressed next.

I. Cross-Construct Correlations and Discriminant Validity at the Pilot Stage

Because each construct was analysed separately, the EFA results establish within-construct dimensionality but provide limited evidence about discriminant validity across constructs. The preliminary correlations bear directly on this question. As a pilot-stage indication, Table 8 reports the inter-construct correlations corrected for attenuation, obtained by dividing each observed correlation between construct means by the square root of the product of the two Cronbach's alpha coefficients. The corrected value approximates the correlation between two constructs measured without error and is conceptually related to the heterotrait–monotrait ratio (Henseler et al., 2015).

Table 8. Inter-construct correlations corrected for attenuation (N = 87)

	PE	EE	SI	FC	SC	VoU	BI
PE	—						
EE	0.683	—					
SI	0.648	1.008	—				
FC	0.797	0.858	0.877	—			
SC	0.737	0.911	0.886	0.924	—		
VoU	0.916	0.827	0.809	0.88	0.879	—	
BI	0.857	0.829	0.849	0.823	0.899	0.995	—

Note: Corrected $r = \text{observed } r / \sqrt{(\alpha_x \times \alpha_y)}$, using the construct-mean correlations in Table 2 and the Cronbach's alpha values in Table 7. Values above .90 in bold.

Source: Prepared by the authors (2026)

Two pairs approach or exceed unity: Effort Expectancy with Social Influence (1.008) and Voluntariness of Use with Behavioural Intention (.995). Three further pairs exceed .90, namely Facilitating Conditions with Smart

Contract (.924), Performance Expectancy with Voluntariness of Use (.916) and Effort Expectancy with Smart Contract (.911), and most remaining pairs exceed .85. On this evidence, the pilot data cannot establish discriminant validity for these pairs, and for Effort Expectancy and Social Influence in particular the data do not distinguish the two constructs.

Three features of the pilot design may contribute to this pattern. First, respondents rated a platform that has not yet been deployed, so their responses may reflect a general favourable disposition toward the concept rather than differentiated beliefs about its attributes, a halo pattern that raises correlations among all constructs. Second, construct means clustered between 8.17 and 8.40 on a ten-point scale, which restricts variance. Third, all measures were collected from a single source at a single point in time, so common method variance cannot be ruled out. For Voluntariness of Use and Behavioural Intention, the item-content overlap discussed in Section IV.F is a further and more specific explanation.

These estimates are approximate. They are based on composite means rather than item-level latent modelling, and alpha-based corrections can over-correct in small samples, which is why one value exceeds 1.0. They do not replace confirmatory testing, but they show where that testing must concentrate. If the problem persists in the field sample, the available remedies include revising items to sharpen the conceptual boundary between Effort Expectancy and Social Influence, removing the Voluntariness of Use items that overlap with intention, or, as a last resort, combining constructs that cannot be separated empirically.

J. Summary of Final Measurement

Given the reduction in item count across several constructs within the proposed theoretical framework, re-labelling is necessary in order to reflect these modifications faithfully. Researchers Hair et al. (2019) note that where a researcher employs factor analysis as a methodological approach, it is both possible and often necessary to substitute the original set of variables with a revised set for the purposes of subsequent analysis.

In the case of Performance Expectancy, the initial set comprised nine items, of which three, namely PE3, PE4 and PE7, were removed, leaving six items which are re-labelled PE1 to PE6 in the final instrument. For Facilitating Conditions, two items, FC7 and FC8, were excluded, leaving six. For Smart Contract, the original batch of ten items was reduced to nine by the removal of SC9. For Voluntariness of Use, three items were eliminated from an initial set of ten, resulting in seven items distributed across two components. Effort Expectancy, Social Influence and Behavioural Intention required no reduction. The decisions to retain or eliminate specific items were informed jointly by exploratory factor analysis and reliability analysis, which together determined the final measures incorporated into the questionnaire intended for the field study. Table 9 summarises the outcome.

Table 9. Summary of the final measurement instrument

Construct	Initial items	Final items	Items deleted	Reason for deletion
Performance Expectancy	9	6	PE3, PE4, PE7	Cross-loading; low loading
Effort Expectancy	9	9	None	Not applicable
Social Influence	8	8	None	Not applicable
Facilitating Conditions	8	6	FC7, FC8	Communality below .50
Smart Contract	10	9	SC9	Low loading,
Voluntariness of Use	10	7	VOU9, VOU10, VOU4	Low loading; cross-loading
Behavioural Intention	9	9	None	Not applicable

Source: Prepared by the authors (2026)

The instrument that emerges is shorter than the initial pool, unidimensional in six constructs and two-dimensional in the seventh, and internally consistent throughout. Its discriminant validity, however, has not yet been established, so confirmatory testing on an independent sample is a prerequisite for, not a formality before,



structural hypothesis testing.

CONCLUSION

This study provides an initial measurement basis for research on blockchain-based waqf endowment in Malaysian public universities, where the administration of waqf continues to be constrained by low efficiency, limited transparency and inadequate accountability in the management of funds. The literature suggests that the four UTAUT factors, namely PE, EE, SI and FC, together with Smart Contract, may influence the intention of millennial alumni to adopt Waqfchain. Smart Contract was added because the automated, conditional enforcement that distinguishes a blockchain-based waqf endowment from a conventional digital donation platform is not captured by the original four constructs. Before these relationships can be tested, the instrument that measures them must be established, and this article reports that first step.

All seven constructs satisfied the requirements for sampling adequacy, with KMO values ranging from .776 to .875 and every Bartlett's test significant at $p < .001$. Six constructs resolved into a single component and one, Voluntariness of Use, into two. Total variance explained ranged from 51.922 per cent to 67.631 per cent, and Cronbach's alpha from .812 to .908. The first objective of this measurement stage, to establish the within-construct factor structure and identify items that fail to load adequately on their intended factor, was therefore met.

Performance Expectancy lost three items and Facilitating Conditions two items with communalities below .50. Smart Contract lost one item from an initial pool of ten and settled into a single component with a narrow loading range, which is consistent with, though not yet proof of, its treatment as a separate construct. Voluntariness of Use required three iterations and resolved into two components, interpreted here as perceived freedom from compulsion and autonomous willingness, the second of which overlaps in content with behavioural intention. Its specification should be decided by comparing competing models in the confirmatory stage rather than assumed. The second objective, to produce a more parsimonious instrument, was achieved; whether that instrument discriminates adequately between constructs remains open.

The most important finding for subsequent work concerns discriminant validity. Corrected for attenuation, the correlations between Effort Expectancy and Social Influence and between Voluntariness of Use and Behavioural Intention approach unity, and several other pairs exceed .90. The pilot evidence therefore cannot show that these constructs are empirically distinct. The confirmatory stage must test discriminant validity using both the Fornell–Larcker criterion and the heterotrait–monotrait ratio and report measurement-model fit indices before the instrument is used to test the structural hypotheses.

The contribution of this stage is therefore methodological rather than substantive. The retained items concern convenience, traceability, trust and fidelity to donor intent, but this reflects which items met statistical retention criteria in a pilot sample, not a finding about what contributors value. Claims about contributor preferences, and about adoption itself, must await the confirmatory and structural stages and, ultimately, data on actual use once Waqfchain is deployed.

The study has several limitations. First, the proposed platform has not yet been deployed, so respondents could not observe it and their responses reflect anticipated rather than experienced use. Second, the pilot sample of 87 valid cases, while meeting the accepted minimum for exploratory factor analysis, is modest and was drawn from the urban central region of Malaysia, so the structure reported here should not be generalised until it is confirmed. Third, because the sample was too small for a pooled analysis, each construct was analysed separately, which limits the evidence on discriminant validity. Fourth, principal component extraction was used; although appropriate for item screening, it analyses total rather than common variance and may overstate loadings, so a principal axis factoring solution should be examined on the field sample. Finally, the study concerns intention to use rather than use itself, and once the platform is developed, a study of actual usage behaviour will provide stronger evidence than a study of intention.

Acknowledgments

The corresponding authors thank the Faculty of Technology Management and Technopreneurship, Universiti



Teknikal Malaysia Melaka, Malaysia. The authors would also like to thank the Ministry of Higher Education Malaysia (MOHE) for the research grant (FRGS/1/2024/FPTT/F00582), and the Centre of Technopreneurship Development (C-TeD) for its support.

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