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Determinants of digital technologies adoption in government census data operations

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Abstract

Purpose – This study investigates the determinants of digital census for population and housing census (PHC) program through the lens of performance expectancy, technology readiness, self-efficacy and hedonic motivation for the upliftment of a national data collection exercise and development of human resource management.

Design/methodology/approach – A quantitative and qualitative research method was used to survey enumerators' responses from the PHC exercise during the COVID-19 period in Ghana. Based on the four determinants, a conceptual framework was developed consisting of eight proposed hypotheses tested through a structural equation model.

Findings – The findings of the study indicate that technological readiness, self-efficacy and hedonic motivation significantly influence behavioural intention to adopt digital technologies for PHC training and data collection. Importantly, the authors identified four key themes relating to digital technologies in PHC – personal enablers, general enablers, inherent affordances (inherent possibilities by the user in relation to what the technology offers in context) and personal inhibitors.

Originality/value – For research, this work systematizes antecedents from diverse research streams and validates their relative impact on government digital transformation for accurate data, thus providing a cohesive theoretical explanation of digital technologies in PHC. Due to the study's infancy in a developing country context, the findings provide a preliminary foundation and constructive insight for a digitalization plan conducive to people's personality and technological readiness.

Keywords Adoption, Digital economy, Technology readiness, Digital technologies, Enablers and inhibitors, Population and housing census

Paper type Research paper

1. Introduction

Since the first outbreak in late 2019, the COVID-19 pandemic has accelerated the adoption and use of digital technologies (Favale, Soro, Trevisan, Drago, & Mellia, 2020; Ofosu-Ampong,

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2021) in national activities, including training census officers for data collection exercises. Most often, developing countries relied on face-to-face training, traditional methods, and a paper-based approach in training and collecting population and housing census (PHC) data. With the technologies deployed, enumerators for the PHC enjoy a range of training resources (quizzes, milestone learning, syllabus, social learning, badges and inquiries) at an appropriate place and time convenient to the users. Recently, Ghana has been ranked (EGDI rank – 101) the first in West Africa and fifth in Africa in e-government development services. The assessment of EGDI indicates a country's strides in infrastructure and educational levels and use of information, technology and communication (ICT) to promote access and inclusion of its citizens. This clearly shows that developing economies are doing well in terms of online services provision, human capacity development for national assignments and telecommunication connectivity. In this regard, national institutions such as the statistical bodies have started taking advantage of the technological prowess to use digital services such as computer-assisted personal interviews (CAPI) to conduct Ghana's first-ever PHC with technology at the hub.

Previous studies have reported the low acceptance and adoption rate of digital technologies in developing countries (Kanwal & Rehman, 2017). As such, deploying technology initiatives face challenges unless the users widely accept it for training and CAPI services as an alternative to the traditional training or paper-based personal interviews (PAPI) approach. In recent times, users are still hesitant to accept new technologies while others discontinue use after initial acceptance as revealed in developing countries (Riffai, Grant, & Edgar, 2012; Kanwal & Rehman, 2017). For example, Africa's digital technologies (learning) market share was valued at US$2.2bn in 2020, accounting for one of the least across the continents (Imarc Report, 2021).

Given the unpredictable and complex learning behaviours, persuading potential field officers of different backgrounds to change their attitude and accept new technology for PHC exercise is challenging, especially in a developing country context. Prior research has reported the issue as one of the most challenging factors in implementing digital technologies in developing countries (Riffai *et al.*, 2012) and requires further investigation to unravel the essential factors that hinder user adoption and intention to use digital census.

Furthermore, recent information systems research has used a meta-analysis to integrate findings from well-established adoption and post-adoption theoretical frameworks such as the technology acceptance model (TAM) (Davis, 1989), unified theory of acceptance and use of technology (UTAUT) (Dwivedi, Rana, Tamilmani, & Raman, 2020), technology-organization-environment framework (TOE) and extended UTAUT2. Notwithstanding the extensive use of the adoption model to explain the use and behavioural intention, few meta-analysis-based papers exist that have integrated the concepts and results. For example, Ambalov (2018) conducted a meta-analysis on 51 studies, whereas Ofosu-Ampong and Acheampong (2022) used structural equation modeling (SEM) to examine the original model of TOE with an additional variable "technology readiness." According to Hunter and Schmidt (2015), there are inconclusive results of studies as it fails to account for mixed results emanating from the meta-deductive analysis.

In this regard, this study includes a mixed-method analysis with a much larger sample size of 206 participants and performs recommended SEM and follows Creswell, Plano Clark, Gutmann, and Hanson (2003) approach for conducting qualitative inquiry in identifying insightful factors and outliers. This study, therefore, examines users' first-time adoption of digital technologies (e.g. CAPI) to facilitate PHC. To achieve the objectives, our study aspires to answer the following research questions:

RQ1. What antecedents influence and motivate enumerators' behavioural intention toward digital technologies in conducting PHC?

RQ2. Does combining constructs of UTAUT2 and technology readiness offers an excellent research framework in the Ghanaian context?

The study is the earliest to investigate enumerators' intentions in census exercise by identifying IT-specific factors that affect the adoption of digital technologies. The study is structured to include the following: literature review, research method and hypotheses, analysis and results, and conclusion.

2. Literature review

2.1 Use of digital census

Investigating technology acceptance and adoption has been established as a relevant aspect of the related literature on online education, such as teaching, personalized and self-regulated learning (McLoughlin & Lee, 2010). Many theories and considerations have been used to investigate and examine critical antecedents of user intention and adoption of e-learning technologies. For example, Kayali and Alaaraj (2020) found that perceived ease of use, social influence, relative advantage and user satisfaction are important predictors of technology adoption in Lebanese universities. The scholars also found a positive influence of behavioural intention on the use behaviour of cloud-based resources. Factors such as utility, usefulness, price value and enjoyment have significantly influenced users' behavioural intention and adoption (Kayali & Alaaraj, 2020; Chen, Li, Liu, Yen, & Ruangkanjanases, 2021). Prior studies have been conducted on behavioural intention and digital media from different perspectives and contexts with different conceptual frameworks. For instance, Table 1 shows studies on digital technologies deployed, the context of the study, the theoretical and methodological models and the factors that may determine digital census adoption.

In Ghana, Boateng *et al.* (2016) empirically investigated students' determinants of e-learning resources using SEM and found perceived usefulness and attitude as significant predictors. Conversely, computer self-efficacy and perceived ease of use were insignificant predictors. In a recent study, Mailizar, Burg, and Maulina (2021) examined how system quality, perceived ease of use, experience, attitude, and perceived usefulness predict adoption during the COVID-19 pandemic. The scholars found attitude as the most significant factor in determining students' technology adoption during the pandemic. Perceived usefulness and ease of use were less significant in predicting behavioural intention because the users had a long experience with the system and were hence conversant with the system. Further, Aboagye, Yawson, and Appiah (2021) supported the adoption challenges of digital technologies from a cultural perspective. They found that accessibility, social, academic, and lecturer issues were the predominant challenges of technology intention and adoption. Lecturer issues were also a hindrance to the intention and use of e-learning. Certainly, these studies have provided an early understanding of determinants of users' behavioural intention and adoption in developing countries. However, other important determinants such as hedonic motivation and technology readiness have received less attention and research in technology adoption.

With the wide adoption of technologies since the pandemic, it has become necessary to expand research to explore other important factors that account for the relationship between technology readiness with self-efficacy and hedonic motivation. These factors have not received much attention in prior research in developing countries. The direct relationship between attitude and behavioural intent and adoption has also been ignored in these studies. Importantly, no study has examined these factors in the context of PHC. Consequently, the motivation of this study is to fill these theoretical gaps and provide new insight into technology adoption in PHC from a developing country context. Thus, we explore the following less researched variables to explain the phenomenon of interest from a developing country's perspective on census: performance expectancy, hedonic motivation, technology readiness and self-efficacy. Lastly, the reviewed papers did not provide a detailed description of the quality of digital technologies deployment, which makes it difficult to understand the IT-specific factors that influence enumerators' and digital census quality. Scholars have been urged to investigate information technology-related factors that are more closely linked to the context of digital technologies (Li, Dai, & Cui, 2020; Damenshie-Brown & Ofosu-Ampong, 2023). This approach may offer more precise recommendations for developing effective strategies, designs and practices (Hong, Chan, Thong, Chasalow, & Dhillon, 2014).

Moreover, in examining prior digital technologies adoption at the organizational level, as noted earlier in Table 1, we identified two drivers as the antecedents. The first driver or dimension is the enablers' factors, a type of external or internal locus of control that motivate

Authors	Theory	Country	Methodology	Some adoption factors
Namisiko, Munialo, and Nyongesa (2014)	Technology acceptance model and Technology, organization and environment	Kenya	Questionnaire distributed to 500 participants Inferential statistics	Technology infrastructure Perceived usefulness Competitive pressure
Boateng, Mbrokoh, Boateng, Senyo, and Ansong (2016)	TAM	Ghana	Surveyed 339 participants Structural equation model	Self-efficacy Attitude Perceived usefulness Perceived ease of use Attitude
Alhabeeb and Rowley (2018)	N/A	Saudi Arabia	Questionnaire distributed to academic staff (230) and students (306) Principal component analysis	Technology infrastructure Ease of access Student characteristics Support and training Instructor characteristics
Yakubu and Dasuki (2019)	Unified theory of acceptance of use of technology	Nigeria	Survey 286 participants Structural equation model	Performance expectancy Effort expectancy
Kayali and Alaaraj (2020)	TAM UTAUT Diffusion of innovation	Lebanon	Questionnaire completed by 422 participants from three universities Smart partial least square	Relative advantage Ease of use Social influence User satisfaction
Chen *et al.* (2021)	UTAUT2	Taiwan	Online questionnaire distributed to 260 participants Partial least squares structural equation modeling (PLS-SEM)	Price value Technological readiness Performance expectancy Facilitating conditions

(*continued*)

Table 1.
Selected studies on digital technologies adoption

Drivers of digital technologies in government and organizational improvement Related papers	Description	Drivers identified
Wimelius, Mathiassen, Holmström, and Keil (2021), Wang, Chen, and Xie (2010), Zhu, Dong, Xu, and Kraemer (2006), Gong, Yang, and Shi (2020), Hafseld, Hussein and Rauzy (2021) and Ofosu-Ampong (2023)	Many government agencies and organizations are utilizing digital technology to enhance business processes and operational performance. For instance, RFID-based technologies are commonly used to transfer data, and mainly to track and identify objects and people to manage the growing complexity of data. Equipment manufacturers employ digital technologies to enable rescheduling, while service managers implement big data analysis to enhance process visibility and transparency, agility and integration While many governments have launched digital transformation initiatives, there is still a lack of understanding about the factors that contribute to their success	Enablers *(triggers that can provoke digital technologies adoption and use)*
Kane (2019), Bharadwaj, El Sawy, Pavlou, and Venkatraman (2013), Ofosu-Ampong (2021), Tangi, Janssen, Benedetti, and Noci (2021) and Simmonds, Gazley, Kaartemo, Renton, and Hooper (2021)	Government institutions are increasingly offering digitalized products and services to better meet market demands and manage customer relationships. In addition to enhancing customer satisfaction, digital solutions can also serve as a powerful government marketing tool, projecting a positive government image as being innovative and digitally savvy. However, the inhabitants may be resistant (inhibitors) to government digital transformation and may impede progress Moreover, digital solutions have the potential to substantially reduce census costs when compared to traditional approaches (paper-based). As a result, many government institutions are striving to adopt the latest digital technologies in order to keep up with digital frontrunners. Organizations that do not follow this trend risk falling behind their competitors	Inhibitors *(barriers to digital technologies use and engagement)*

Source(s): Indicate by authors

Table 1.

people to engage in counterproductive work behaviour. Thus, if the adoption of technology does not meet the performance and effort expectancy of the intended users, it may lead to counterproductive work behaviour. Venkatesh, Cheung, Davis, and Lee (2021) consider enablers as an internal propensity or external pressure that motivates work outcomes while the second driver, i.e. inhibitors, are barriers that prevent “deviant behaviour”.

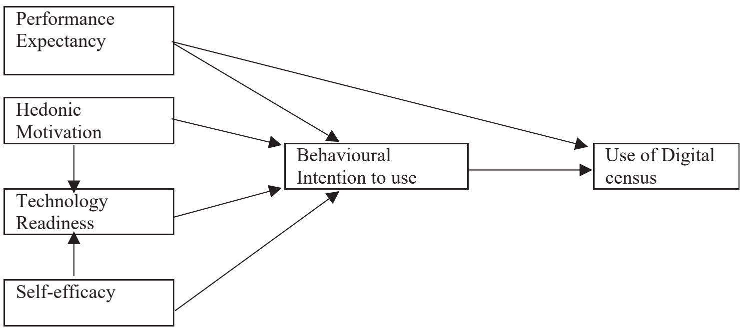
The conventional research on information systems (IS) has predominantly concentrated on identifying the factors that promote technology usage (i.e. enablers) while giving less consideration to the factors that deter it (known as inhibitors). However, we believe that enablers and inhibitors are separate concepts and can exist together. Examining IT usage from both enabler and inhibitor perspectives can offer a more comprehensive understanding of this phenomenon (Cenfetelli & Schwarz, 2011).

3. Research model and hypothesis

As shown in Figure 1 are four determinants (performance expectancy, hedonic motivation, technology readiness, and self-efficacy) for predicting behaviour intentions included in the proposed conceptual model. The hedonic motivation and performance expectancy as an extension of the unified theory of acceptance and use of technology was proposed to address the technology adoption from the user perspective (Venkatesh *et al.*, 2012). Similarly, technology readiness and self-efficacy have been widely used. Extant literature shows its predictive power of analysing users' intention and adoption of emerging technologies (Kuo, Liu, & Ma, 2013; Chen *et al.*, 2021). The next section discusses the research model and hypotheses development.

3.1 Performance expectancy

Originally, Venkatesh *et al.* (2012) defined PE as the extent to which individuals believe that their job performance is improved using technology. However, depending on the nature of their research, several researchers (such as Sewandono *et al.*, 2022; Batucan *et al.*, 2022) have explored PE from a different viewpoint concerning habitual behaviour. For this study, we define PE as the degree to which the use of digital census tools (such as CAPI) has enabled enumerators to effectively carry out their duties. As a relatively new area of study, there may not be any prior research that specifically examines the relationship between PE and digital census. However, PE has been used in other studies to establish its relationship with various technology outcomes, such as faculty research, where Sewandono *et al.* (2022) found that information quality, collaboration quality, and satisfaction with system use all have a positive and significant relationship with PE. Using the extended UTAUT model to explain factors affecting online technologies, Batucan *et al.* (2022) concluded that there was an insignificant relationship between PE and BI, but they explained that the level of interactivity



Source(s): Adapted: Parasuraman (2000), Compeau and Higgins (1995) and Venkatesh *et al*. (2012)
Authors elaboration

Figure 1.
Research model of digital census adoption for PHC

the system affords and the actual enjoyment from the system can significantly influence PE. Despite their findings, this study seeks to explore the relationship between PE and digital census specifically, and the following hypothesis is proposed:

H1. PE influences BI.

H2. PE influences the use of digital census.

3.2 Hedonic motivation

HM refers to the happiness or pleasure from using an innovation (Venkatesh *et al.*, 2012). Previous studies (Nguyen, Nguyen, Pham, & Misra, 2014) have found the positive influence of HM on users' behavioural intention to use digital technologies and the essential role HM plays in technology acceptance (Venkatesh *et al.*, 2012; Chen *et al.*, 2021). Similarly, Raman and Don (2013) found HM as a significant predictor of BI among teachers learning management systems. Prior studies have also found that HM factors such as enjoyment, excitement, playfulness and fun are influential factors in predicting users' intention to adopt e-learning services (Riffai *et al.*, 2012; Chen *et al.*, 2021). Also, the relationship between HM and TR has been established in the literature (Borotis, Zaharias, & Poulymenakou, 2008) to mean that users who perceive e-learning as exciting tend to be more technologically ready and competent to use e-learning services. In recent times, gamification (Ofosu-Ampong, 2020) – an act of adding game design elements to task activities to improve the hedonic value of systems is been propagated in most organizations. To this end, the study proposes the following:

H3. HM influences BI.

H4. HM influences TR.

3.3 Technological readiness

TR is the extent to which human capacity, technological infrastructure, and innovation support technology adoption (Wang *et al.*, 2010). Human resource or capacity readiness is the skills and knowledge required to manage and implement e-learning services for PHC. On the other hand, the technological infrastructure is the hardware, software, and services required to manage and operate e-learning services in a national assignment. Thus, the IT skills of users and the availability of technological infrastructure and innovation products constitute TR of a PHC and may influence the adoption of e-learning (Wang *et al.*, 2010; Oliveira & Martins, 2010). Consequently, TR is important in behavioural intention to adopt e-learning. Thus, the study proposes the following:

H5. TR influences BI to use digital census.

3.4 Self-efficacy

SE refers to how individuals judge their capabilities to perform a task. As people will operate and manage e-learning services if adopted for data collection and training, their capability for the exercise is a factor that may influence e-learning adoption (Oliveira & Martins, 2010). Thus, several studies (Sharif & Raza, 2017) have found a positive relationship between SE and BI. Further, SE can indirectly contribute to BI by shaping the users' perception (e.g. ease of use and technology readiness) towards an innovation (Pan & Jang, 2008). According to Wang *et al.* (2010), users who believe in their skills and abilities to use technology are more likely to adopt such innovation. Accordingly, users may be more technologically ready if they positively perceive their self-efficacy and capability to use e-learning services appropriately. As a result, SE is critical in the use of technologies. Thus, the study proposes the following:

H6. SE influences BI.

H7. SE influences TR.

3.5 Behavioural intention

BI is "a cognitive process of individuals' readiness to perform specific behaviour and is an immediate antecedent of usage behaviour" (Abbasi, Chandio, Soomro, & Shah, 2011). Prior studies have found BI as an essential determinant of technology acceptance and success of a system and a decisive drive of actual use behaviour (Tarhini, Hone, & Liu, 2014; Alalwan, Dwivedi, & Rana, 2017). Thus:

H8. BI influences the use of digital census.

3.6 Methodology

The protocol for this study was reviewed by the District Census Office of the Kwaebibirem Municipal Assembly of Ghana. A mixed research method was used for this exploratory study to include a survey questionnaire and interviews.

The purpose of the study is to investigate the determinants of behavioural intention and adoption of digital technologies in census. This is the first time Ghana is employing DT in PHC, hence the issues of technology acceptance or rejection may be diverse and not clear-cut. To ensure reliability and validity of the survey instruments and importantly collect quality data, the study followed Churchill (1979) approach used for designing the questionnaire. The works of Compeau and Higgins (1995), Parasuraman (2000) and Venkatesh *et al.* (2012) informed the item selections for SE, TR, PE and HM. Table 2 provides a conceptualization of the constructs used in this study. The target population are enumerators recruited by the Ghana Statistical Service to partake in the PHC which is conducted every 10 years. A convenience sampling technique was adopted to make use of readily available enumerators after the fieldwork. The researchers were added to the WhatsApp platform created for the enumerators. In all, two WhatsApp platforms were created with each consisting of 170 members. Formal consent was sought from the participants and our objective for the study was made known to them. Since the researchers were in the field, most participants wanted to fill out the questionnaire via paper-based, so their phone numbers were collected on the platform for face-to-face data collection. Others preferred the online questionnaire due which was the most convenient. This approach to collecting data is deemed best due to COVID-19 protocols. The paper-based and online data collection was carried out from June to July 2022 in the Eastern part of Ghana (Koforidua and Kade). A total of 216 respondents were obtained, and 206 were useable, i.e. 10 invalid responses. The study used a 5-point Likert scale, ranging from strongly agree (1) to strongly disagree (5). Structural equation modeling (SEM) using SPSS and SmartPLS was used in analysing the data.

4. Results

4.1 Descriptive statistics

Out of the 206 participants, 54.4% were male, while 45.6% were females. The ages of the respondents ranged from 22 to 67, with a mean age of 38.5. Majority of the participants were senior high school and diploma holders (46.8%), bachelor's degree holders (32.3%), senior high certificates (17.7%) and master's degrees (3.2%). Further, 41.7% of the enumerators were unemployed, 10.4% were teachers, 10.4 were health workers and 6.3 were retired. Ghana has a relatively high unemployment rate as supported by our data. According to the Ghana Statistical Service's Labor Force Survey Report for 2019, the unemployment rate was 7.3%. However, it is worth noting that the youth unemployment rate is much higher than the overall

Factors	Item	Sources
Performance expectancy	The use of digital technologies would enhance job performance The degree to which new technologies are perceived as better than previous innovation Digital technologies are useful in daily transactions and involve personal consequences of the behaviour	Modified (Alalwan *et al.*, 2017)
Hedonic motivation	Using the digital census is fun with good design Using the digital census is entertaining and relaxing for learning and data collection The badges and game elements were fun and engaging	Modified (Venkatesh *et al.*, 2012)
Self-efficacy	My interaction with the digital census is good and easy to use I think using digital census meets my skills and competences	Modified (Compeau & Higgins, 1995)
Technology readiness	Digital census contributes to quality data and gives me more freedom of mobility The training was adequate and gives me more control I think the digital census was not designed for use by ordinary people	Modified (Wang *et al.*, 2010; Oliveira & Martins, 2010)
Behavioural intention	I intend to continue using digital census in the future for training and data collection I will always opt for a digital census for data collection than paper-based	Modified (Venkatesh *et al.*, 2012)
Use behaviour	Kindly indicate your usage frequency for the following digital census features: Tablets E-learning Location	Modified (Oliveira, Alhinho, Rita, & Dhillon, 2017)

Source(s): Indicate by authors

Table 2. Conceptualisation of the constructs

rate, with 13.8% of young people aged 15–24 unemployed. Despite efforts to create jobs and reduce unemployment, it remains a significant challenge for the country. Interestingly, out of the 206 enumerators, only 64 (31.1%) own a tablet. In contrast, 142 (68.9%) have used a tablet before but do not own one. Table 3 shows the demographic characteristic of the respondents.

Furthermore, most of the participants were at the beginner's stage of using data collection software; on the contrary, majority of the enumerators (67.5%) have intermediate experience with tablet and ICT knowledge. Consequently, intermediate and advanced knowledge and experience with ICT and tablets do not necessarily equate to experience in data collection software.

4.2 Quantitative inquiry

There are two parts to the results. The first part of the results (i.e. quantitative analysis) is in two folds. The first is the measurement model validation, where the variables of the psychometric properties were examined. The second is the structural model assessment where collinearity issues, predictive relevance and the relationship between the constructs were examined.

4.3 Assessment of measurement model

To evaluate the measurement model, we examine the reliability, convergent validity and discriminant validity. The study followed three steps (Fornell & Larcker, 1981). First, all the

	Characteristics	N	%
Gender	Male	112	54.4
	Female	94	45.6
Age	22–32	74	36.9
	33–43	89	43.2
	44–54	31	15.0
	55–67	10	4.9
Educational level	Senior High/Diploma	109	52.9
	Bachelor's degree	72	35.0
	Master's degree or above	25	12.1
Experience with Tablet/ICT knowledge	Beginners	30	14.6
	Intermediate	139	67.5
	Advanced	68	33.0
Profession of enumerators	Trained teachers	48	23.3
	Retired (e.g. educationists)	13	6.3
	University students	10	4.9
	Unemployed	86	41.7
	Traders	7	3.4
	Health personnel	42	20.4
Data collection software used by enumerators	Beginners	133	64.6
	Intermediate	61	29.6
	Advanced	12	5.8

Source(s): Indicate by authors

Table 3. Demographic characteristics

item loadings must be above 0.6. Second, the composite reliabilities (CR) should be higher than 0.8. Finally, the average variance extracted (AVE) must be above 0.5. As shown in Table 1, the analysis of the results confirms that all the item loadings were higher than the 0.6 thresholds. Also, as indicated in Table 4, the CR values were equal to or higher than 0.850 except for PE (0.809), and the AVE value was between 0.592 and 0.769. This implies that convergent is fulfilled.

The reliabilities of the latent variables were assessed using the CR and AVE with values above 0.8 and 0.5, respectively. As shown in Table 4, the reliability of CR and AVE is acceptable and confirms the measurement model's reliability. The discriminant validity is assessed using the Heterotrait-Monotrait ratio of correlation (HTMT). HTMT values equal to or less than 0.9 indicate discriminant validity is established. As shown in Table 5, all the values were below 0.9 except HM and behavioural intention which equalled the 0.9 thresholds, however, remain unaffected because the threshold is 0.9 and below. Consequently, the measurement items indicate the model fitness of the proposed research. It is important to establish the fact that there is evidence of an estimated correlation between measures as some values are close to 0.9 in Table 5 (Bagozzi & Phillips, 1982).

4.4 Assessment of structural model

The structural model in an SEM specifies the hypothesized relationships among the latent variables, and also the relationships between the latent and observed variables. The structural model and hypothesis are analysed based on the calculated values of the path coefficient and t-values. The R^2 indicates the model's predictive capabilities. The strength of the R^2 for BI of digital census usage (dependent variable) indicates that three independent variables (i.e. HM, TR, SE) explain 73.8% of intention to use. At the same time, BI accounted for 68.2% of the actual use of digital census variance. Multi-collinearity issue is also assessed using the VIF statistics. VIF values less than 5 indicate no collinearity issue (Hair, Sarstedt,

Constructs	Label	Loadings	Cronbach's alpha	rho_A	CR	AVE
Digital Census Adoption	DCA1	0.861	0.760	0.787	0.860	0.674
	DCA2	0.848				
	DCA3	0.746				
Behavioural Intention	BI1	0.865	0.813	0.784	0.861	0.675
	BI2	0.882				
	BI3	0.704				
Performance Expectancy	PE1	0.766	0.696	0.800	0.809	0.592
	PE2	0.910				
	PE3	0.607				
Hedonic Motivation	HM1	0.860	0.732	0.758	0.850	0.656
	HM2	0.876				
	HM3	0.679				
Self-efficacy	SE1	0.880	0.701	0.703	0.870	0.769
	SE2	0.874				
Technology Readiness	TR1	0.750	0.769	0.822	0.864	0.681
	TR2	0.893				
	TR3	0.826				

Source(s): Indicate by authors

Table 4. Construct reliability and validity

	Adoption	Behavioural intention	Performance Expectancy	Hedonic motivation	Self-efficacy	Technology readiness
Adoption						
Behavioural Intention	0.891					
Performance Expectancy	0.115	0.355				
Hedonic Motivation	0.897	0.900	0.223			
Self-efficacy	0.810	0.824	0.278	0.767		
Technology Readiness	0.712	0.881	0.305	0.801	0.539	

Source(s): Indicate by authors

Table 5. Discriminant validity - HTMT

Hopkins, & Kuppelwieser, 2014). As shown in Table 6, all the values ranged from 1.062 to 2.683 implying that the issue of multi-collinearity was not present.

The statistical significance of the propositions is achieved using the bootstrap resampling method (Henseler, Ringle, & Sarstedt, 2015). Table 7 illustrates the support of the hypothetical path of the adapted model. Out of the eight hypotheses, H1, H3, H4, H5, H6 and H8 indicate a strong positive effect, while H2 and H7 are not supported. Consequently, HM (t-value = 3.475), technological readiness (t-value = 4.090) and SE (t-value = 2.210) show a positive effect on enumerators' intention of digital census usage. Enumerators' behavioural intention (t-value = 25.285) also shows a positive effect on the digital census in PHC.

Moreover, PE (t-value = 2.899) affected participants' behavioural intention to use and use digital census (t-value = 3.582). The result of HM on TR is t-value = 9.731. The results support the hypothesis and thus HM positively impacts TR to adopt digital technologies in PHC. On the other hand, self-efficacy had no positive effect on TR (t-value = 0.013) of enumerators BI to adopt. The final findings of the SmartPLS analysis are shown in Figure 2.

Table 6.
Collinearity statistics (VIF)

	Adoption	Behavioural intention	PE	Hedonic motivation	Self-efficacy	Technology readiness
Adoption						
Behavioural Intention	1.062					
Performance Expectancy	1.062	1.048				
Hedonic Motivation		2.683				1.476
Self-efficacy		1.477				1.476
Technology Readiness		2.267				

Source(s): Indicate by authors

Table 7.
Hypothesis confirmation and effect size

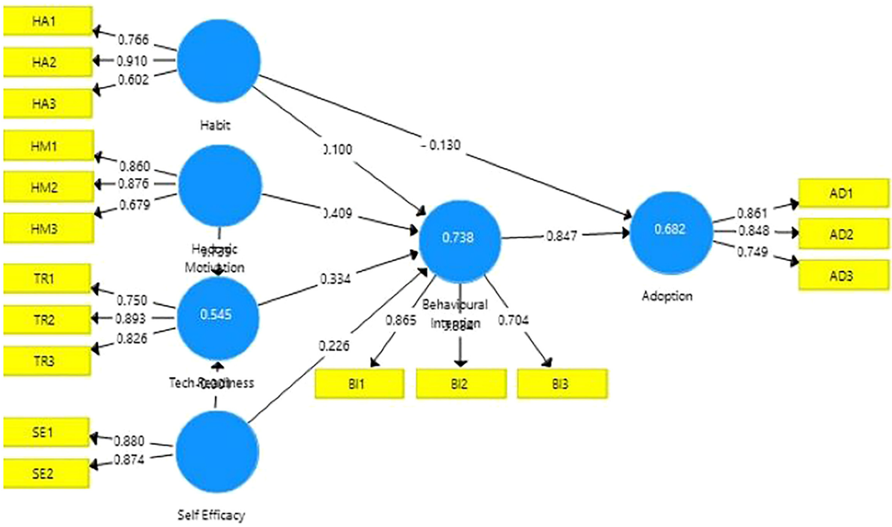
Path	Path coefficient	SE	f^2	*t* value	Support
Performance Expectancy → Behavioural Intention	0.100	0.083	0.137	2.899	H1: Supported
Performance Expectancy → E-Learning Adoption	−0.130	0.078	0.150	0.358	H2: Not supported
Hedonic Motivation →Behavioural Intention	0.409	0.118	0.238	3.475	H3: Supported
Hedonic Motivation →Technological Readiness	0.739	0.076	0.813	9.713	H4: Supported
Technological Readiness → Behavioural Intention	0.334	0.082	0.188	4.090	H5: Supported
Self-efficacy → Behavioural Intention	0.226	0.102	0.133	2.210	H6: Supported
Self-efficacy →Technological Readiness	−0.001	0.088	0.00	0.013	H7: Not supported
Behavioural Intention → Digital Census Adoption	0.847	0.034	2.124	25.285	H8: Supported

Source(s): Indicate by authors

Additionally, we estimated the goodness of fit indices using standardized root mean square residual (SRMR) and normed fit index (NFI). The SRMR measures the approximate fit index, and its acceptable range is between 0 and 0.08 with a comparative fit index (CFI) > 0.95 (Hu & Bentler, 1998). The NFI which shows the incremental fit indices indicates that the closer the NFI value to 1, the better the fit (Hu & Bentler, 1998). Table 8 shows the CFI, SRMR and NFI values of the model fit. The SRMR value (0.081) was slightly higher than the 0.08 threshold. This can occur if there is missing data; however, SRMR ≤.09 may still be indicative of an acceptable fit (Little, 2013). This study assumed a 95% confidence interval, with a minimum critical value of 1.65 for a significance level of 10% (two-tailed). The estimated model in the SEM represents the statistical findings and results based on the observed data, which provides insights into the structure and relationships of the variables under analysis in this research.

4.5 Qualitative inquiry

The second part is the results from the interview held with the enumerators on the digital census to respond to the call for incorporating particular variables necessary for the uptake of



Source(s): SmartPLS output

Figure 2. SmartPLS analysis results

	Structural model	Estimated model
CFI	0.910	0.952
SRMR	0.067	0.081
NFI	0.791	0.889

Source(s): Indicate by authors

Table 8. Model fit

technologies in the census. IT-specific constructs are rarely found in prior PHC studies. The interview on the digital census was to map out specific IT variables and sub-constructs relevant to technology adoption. This helps to broaden the UTAUT model inadequacy and explain the phenomenon of interest (see Table 9). As an explanation of the observed phenomenon and a guiding theory (UTAUT) in this study, our sub-constructs are contextually developed from the interview and should serve as a contribution to the theory in describing the main tenants. The digital census was found to be effective and empowered enumerators to accomplish training and data collection activities in a reduced time. The qualitative data were collected at roughly the same time as the quantitative data. This implies that the same respondents were selected for the quantitative and qualitative for easy convergence and thematic trend of analysis. Selecting different respondents would have introduced personal characteristics that might confound the measures and results.

In essence, this study followed Creswell *et al.* (2003) approach to conducting and evaluating quantitative and qualitative research. Following Creswell *et al.* (2003), we derived the first-order codes, second-order themes and aggregated dimensions (Gioia, Corley, & Hamilton, 2013). The classification is based on a data structure that groups first and second-order themes within the three aggregate dimensions of *personal enablers, inherent affordance, general enablers and personal inhibitors* (Figure 3). This was to allow the researchers to gather additional data to understand the phenomenon and help resolve technology adoption contradictions. After the data analysis, the team concluded that digital technology adoption

Table 9.
Use of digital census: qualitative inquiry and thematic analysis (n = 10) on IT-specific variables

UTAUT2/Technology acceptance factors (first-order codes)	Sub-construct (second-order themes)	Occurring themes (exposition) *(use and intent-to-use the digital census was influenced by. . ..)*	Four core identified themes (aggregated dimensions)
Performance expectancy	Job fit and perceived usefulness	Accurate data emanating from digital census • More accurate and reliable than the paper-based approach Direct assistance from supervisors and district census officer and monitoring team Reduced time to complete tasks – improved efficiency compared to the previous census	***Personal enablers*** The attitude towards technologies in PHC – thus, the degree to which an enumerator has a favourable evaluation of digital census
	Perceived behavioural control	Social support and try-out opportunities Digital literacy Persistent use boost confidence	
	Outcome expectations/ enablers	Safety of use and privacy control of devices Increased self-esteem of enumerators	
Hedonic motivation	Intrinsic motivation	Pride partaking in the digital census	***Inherent affordances*** These are inherent possibilities by the user in relation to what the technology offers in context. Hence the affordance may emanate from digital, institutional or social
	Relative advantage	Household benefits: reduced time in counting, convenience, accessible Counting accuracy: more accurate and prompt errors Reduce the time to complete a household Device portability	
	Extrinsic motivation	Increase trust with data and information from households (enumerators were mostly recruited from the zonal communities) Cases of census are resolved quickly due to the familiarity of enumerators Census participation incentives	

(*continued*)

UTAUT2/Technology acceptance factors (first-order codes)	Sub-construct (second-order themes)	Occurring themes (exposition) *(use and intent-to-use the digital census was influenced by. . ..)*	Four core identified themes (aggregated dimensions)
Technology readiness	Perceived ease of use	Easy to use due to prior experience with technologies Training was not sufficient and prior experience with technology is key to digital census success Recognized first-time challenges but adapted with time Ease of work due to "all-in-one" census data and device	***General enablers*** Focus on the organizational capacity to initiate digital technologies to affect traditional business operations and produce transformational change (sometimes through hybrid)
	Compatibility	Technologies and manuals were intended for the census program and officers *According to* (Ofosu-Ampong & Acheampong, 2022) *compatibility plays a critical role when an organisation evaluates new technologies to see if there is an overlap with the perceived ease of use and usefulness of technologies as experienced in the past* • *Familiarity and compatibility with social lifestyle and reliability* • *Organizational readiness and top management support* • *Market Dynamics and competitive pressure for conducting population census*	
	Optimism	Generally have a positive view of technology • Offers *increased control, flexibility and efficiency in digital census* • *Increased efforts to attain desired goals and outcomes of the census* • *B*usiness model readiness and government support	
	Innovativeness	Keen to adopt new technologies • Willing to operate as key change agents to facilitate digital census *Challenge: some expressed discomfort/insecurity towards the technology that emanates from general scepticism towards the ability of digital census to work appropriately*	

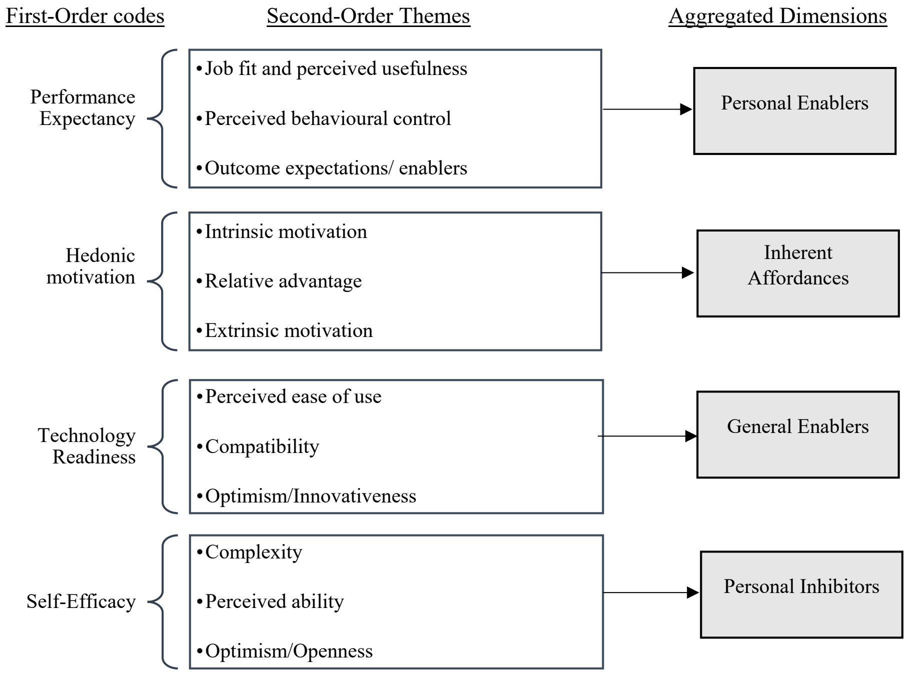
(*continued*)

Table 9.

UTAUT2/Technology acceptance factors (first-order codes)	Sub-construct (second-order themes)	Occurring themes (exposition) *(use and intent-to-use the digital census was influenced by. . ..)*	Four core identified themes (aggregated dimensions)
Self-efficacy	Complexity	The majority were early adopters of the digital census, especially the software for collecting the data Ease in performance of the task (data collection) Confidence with time; Data security	***Personal inhibitors*** Refers to enumerators' propensity to try innovations or technologies, notwithstanding the technological challenges. Hence, have a high sense of openness, flexibility and optimism
	Perceived ability	Efficacy belief – perceived skills, competence and characteristics with the digital census (perceived benefit)	
	Optimism/ openness	Enumerators perceived the digital census as more competent in training than on the field for data collection	

Source(s): Indicate by authors

Table 9.



Source(s): Ofosu-Ampong

Figure 3. Overview of data structure

can be grouped into different user types. We, therefore, turned to the qualitative data, where we highlighted four qualitative themes and re-examined their quantitative occurring indicators for support for the themes. The new information led to further analysis of the literature, in which we found sub-constructs confirmation for the new findings. As shown in Table 9, the quantitative data were collected first, and the results of the technology acceptance (UTAUT2) factors informed the qualitative form of data collection, analysis and insight. The occurring themes show a summary and highlight the interview responses. Accordingly, we summarized their responses by first giving sub-constructs and eventually the four core themes. These sub-constructs, to be measured directly or indirectly by those occurring themes, can be used in studies of a similar kind in the future.

We identified 13 sub-constructs and several occurring themes on the use and intent-to-use digital census in a developing country. Regarding performance expectancy, three constructs were identified namely job fit and perceived usefulness, perceived behavioural control and outcome expectation of digital census. Some of the recurring themes include social support and try-out opportunities, persistence use boost confidence and digital literacy as a primary factor in technology adoption. Hedonic motivation revealed three constructs while technology readiness showed four constructs. Regarding self-efficacy, three constructs namely complexity, perceived ability and optimism were identified. These constructs allowed us to explore further the occurring themes as shown in Table 9.

Importantly, we identified four key themes relating to digital technologies in PHC – personal enablers, inherent affordances, general enablers and personal inhibitors. These themes are distinctive to digital innovation at the national level and could form a conceptual initiative that allows for connections between national initiative, regional acceptance and district-level implementation of digital technologies. Thus, we found that during a pandemic, the human resource management of technology for a national assignment may exhibit these four personality traits and future studies may examine technology use in these dimensions.

5. Discussion

Looking at users' behavioural intention and adoption of technologies, this study presents a significant contribution to existing knowledge regarding digital technologies for PHC training and data collection. Certainly, the study provides practitioners and researchers with an understanding of key determinants and aspects of integrating technology to collect information from over 30 million population. The study extends previous constructs on technology adoption and goes beyond proposed studies examined by considering new constructs (HM), including SE and TR. It further investigates the causal path between BI and the use of digital census. From the analysis, the proposed model successfully predicted 73.8% of the variance in BI. This large portion of variance is close to Venkatesh *et al.*'s (2012) predictive value of 74%. Consequently, this shows how solid the conceptual model predicts the field officers' intention and adoption of digital technology in the era of COVID-19. The study also found four key themes necessary for understanding digital technologies adoption. They include personal enablers – the degree to which an enumerator has a favourable evaluation of digital census; inherent affordance – these are inherent possibilities by the user in relation to what the technology offers in context; while general enablers focus on the organizational capacity to initiate digital technologies to affect the traditional business operation and produce transformational change. The last theme is personal inhibitors which refer to enumerators' propensity to try innovations or technologies, notwithstanding the technological challenges.

Empirically, the relationship between HM and BI and TR is the most significant. This means that enumerators in the PHC fancy excitement and fun in using DT and are more motivated to train and collect effective census data with technology such as CAPI. These results are consistent with prior studies (Riffai *et al.*, 2012; Venkatesh *et al.*, 2012; Farooq *et al.*, 2017). Accordingly, the national statistical units should promote more data collection technologies and continue developing enumerators' skills and experience to use DT effectively in subsequent PHCs. As the results revealed that SE positively affects BI, conducting PHC training for field officers will enhance their self-efficacy and intention to use DT (Compeau & Higgins, 1995).

In most developing countries, using digital means such as tablets for training and data collection represents an added value in terms of innovation, improvement, and modernization. Hence, this approach contributes to the intrinsic motivation of users to effectively collect quality data for projection and resource allocations. Riffai *et al.* (2012) found the essential function of intrinsic motivation in predicting behaviour intention. This study finds similarities in a developing country context. TR is the second strongest factor predicting BI, indicating that in conditions of a high level of TR, enumerators will have a stronger reason to adopt digital technologies. In this regard, enumerators with high TR will achieve a higher productivity benefit and stronger training intention with the technology. Further, HM positively influences TR, whereas SE negatively influences TR.

Finally, SE was found to influence BI positively. The result of this finding is consistent with prior studies (Zhou, 2012; Alalwan *et al.*, 2017). This implies that field officers capable of using technologies for training and data collection are more likely and motivated to use the technology for PHC and in the future. Accordingly, enhancing the enumerators' self-efficacy – skills and experience will result in the intention to use digital technologies (Compeau & Higgins, 1995) and ultimately collect quality data. Further, users with high innovativeness have a better understanding. Thus, they are more willing to learn and use new technologies and become familiar operators of the product than users with less drive for innovativeness (Massey, Khatri, & Montoya-Weiss, 2007).

5.1 Theoretical implications

This article makes a valuable contribution to the IS literature by addressing the gaps that exist in digital census research. Specifically, we identified and organized the antecedents of the digital census, which is a significant contribution to the literature and theory building. We utilized a literature-based approach to synthesize four theoretical construct perspectives (guided by the UTAUT2), namely performance expectancy, hedonic motivation, technology readiness and self-efficacy, into a comprehensive model. This approach provides a unified and cohesive explanation of the digital census, which is in line with calls from IS scholars to create unified models that synthesize diverse theories and models. This paper's contribution aligns with previous research by Ofosu-Ampong and Acheampong (2022) and Venkatesh *et al.* (2012) that advocate for a unified approach to advance the IS field. This study is one of the initial research to evaluate the acceptance and use of digital census among enumerators in a developing country, particularly after the outbreak of COVID-19, using a distinctive research model. Our model also allowed for the exploration of second-order themes and aggregated dimensions of the qualitative inquiry, such as Job fit and perceived usefulness, compatibility, innovativeness, perceived ability and optimism.

5.2 Practical implications

Practically, as national assignments increasingly rely on digital technologies for operations, our work confirms that personal enablers, general enablers, inherent affordances and personal inhibitors can significantly affect work activities and performance. Thus, directors or managers must pay attention to job fit, perceived usefulness, relative advantage, innovativeness and perceived behavioural control of employees for short-term contracts. By uncovering the four core themes on the use of digital census for national assignment, we offer countries planning on census and population exercises insights on how to tailor technologies to provide accurate data for national projections. Also, given the importance of readiness in such a huge task, managers must deploy the technologies and training of required staff earlier to the district and regional zones. This will help in paying close attention to high-priority areas with less technology readiness and extraversion – as their engagement with non-work digital technologies use is likely to be high.

6. Conclusion

This study contributes to the understanding of behavioural intention and adoption of digital technologies for PHC training and data collection. It highlights the key determinants and aspects of integrating technology to collect information from over 30 million populations. The study uses new constructs such as HM, SE and TR to extend previous constructs on technology adoption. From the analysis, the proposed model predicts the field officers' intention and adoption of digital technology. The study also identifies four key themes necessary for understanding digital technologies adoption. These include personal enablers, inherent affordances, general enablers and personal inhibitors.

The study finds that HM and TR are the most significant factors predicting BI, indicating that enumerators in the PHC fancy excitement and fun in using DT and are more motivated to train and collect effective census data with technology such as CAPI. The study recommends that the national statistical units should promote more data collection technologies and continue developing enumerators' skills and experience to use DT effectively in subsequent PHC.

SE is found to influence BI positively, implying that field officers capable of using technologies for training and data collection are more likely and motivated to use the technology for PHC and in the future. Practically, the study recommends that directors or managers pay attention to job fit and perceived usefulness, relative advantage, innovativeness and perceived behavioural control of employees for short-term contracts.

7. Limitations and future research

The suggested future research directions can contribute to addressing the limitations of the current study and expanding the knowledge in the field of digital census adoption in developing countries. Conducting studies in other developing countries can increase the generalizability of the findings and provide insights into the similarities and differences in the adoption of digital census technologies in different contexts.

In addition, using qualitative research methods can complement the quantitative findings and provide a more in-depth understanding of the determinants of digital census adoption in developing countries. Qualitative studies can help identify additional factors that may not have been captured in the quantitative approach and explore the nuances and complexities of the adoption process.

Furthermore, examining the impact of demographic differences on the independent variables of use intention can enhance the understanding of how digital census technologies are perceived and adopted in developing countries. This can help inform targeted interventions and policies that address the specific needs and preferences of different demographic groups.

Overall, these future research directions can contribute to advancing the knowledge and understanding of digital census adoption in developing countries, which can have important implications for improving census data collection and management processes.

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