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Digital Health Application Adoption among Community Health Workers in Bangladesh: The Roles of Task-Technology Fit and Institutional Support

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ABSTRACT

This study analyzes the digital health application adoption in community health workers in Bangladesh by incorporating the task characteristics, technology characteristics, institutional support, task-technology fit, and digital health application adoption in a PLS-SEM framework. This survey involved a group of 530 community health workers in health institutions in a cross-sectional survey. Partial least squares structural equation modelling was used to analyse the data to determine the measurement model, structural relationships, mediation, explanatory power, and predictive relevance. The results established indicator reliability, internal consistency, convergent, and discriminant validity. There were positive and significant impacts on task-technology fit on task characteristics, technology characteristics and institutional support. Task-technology fit and institutional support also had positive and significant effects on digital health application adoption. Task function technology fit has become the most significant direct predictor of adoption whereas the technology characteristics became the most significant predictor of task technologies fit. We found that task-technology fit was found to transmit the impact of both task characteristics and technology characteristics on the adoption process. The model explained 46.2% of the variance in task-technology fit and 48.2% of the variance in digital health application adoption. Positive values of the predict Q2 and reduction in the prediction error as compared to the benchmark verified predictive relevance. The paper reveals the necessity of quality applications, alignment of tasks, training, infrastructure and the consistent support of the institutions.

INTRODUCTION

Community-level healthcare is being increasingly supported through the use of digital health applications (Akhtar *et al.*, 2025). These applications may help health workers in registering patients, collecting household data, clinical documentation, managing referrals, providing health education, disease surveillance, appointment monitoring and communication with health facilities (Asif Akhtar *et al.*, 2024). They are especially applicable in an environment where health services need to serve scattered groups with less physical and human resources. The community health workers play a significant role in the healthcare system of Bangladesh. They tend to link the households to communal clinics, hospitals, family planning services, maternal health programmes, immunisation services, and public health campaigns (Blondino *et al.*, 2024). The parameters of their operations demand frequent interaction with patients, community, supervisors, and healthcare facilities. The collection and transmission of masses of health information are also included in the work (Islam *et al.*, 2024). These processes can be enhanced through digital health applications that will substitute the paper records which are most of the times fragmented with information systems that are more accessible and faster.

Nonetheless, the presence of a digital application does not necessarily guarantee its uptake (Greuel *et al.*, 2023). When an application does not align with the job of

community health workers, they may avoid using it or use it inconsistently. Applications can fail as well when they are hard to use, unreliable, not accessible in the field, or do not deliver the information needed to deliver a service (Santos *et al.*, 2025). Thus, it is not simply the presence of technology that is required in the process of adoption. It is determined by the fitting of the technology to the work that the users need to carry out.

This relationship can be explained with the help of task-technology fit (Haq *et al.*, 2024). It is a measure of the alignment of technological capabilities with the needs of tasks of a user. There is a good fit where the application assists in field work, enhances accuracy, saves time in reporting, coordinates and makes information relevant. A bad fit happens when the application produces extra work or fails to match with the known work flows (Wasunna & Holean, 2021).

External support is also required. The community health workers often rely on the organisations to supply them with equipment, mobile data, training, supervision, technical support and specific implementation guidelines (Rodrigues *et al.*, 2022). A well-designed application is unlikely to be adopted in the case when the workers do not have the operational resources or when the management does not support them. Tasks-technology fit can also be enhanced through institutional support that enables users to learn how the application can fit into their daily work (Sulyaprilawati Battri Siahaan & Marice Simarmata, 2025).

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Much of the past research on digital health adoption usually focuses on individual attitudes, perceived usefulness, ease of use, or behavioural intention (Zaman *et al.*, 2025). These considerations matter, yet not completely determine whether a digital tool will be functionally suitable to community health work (Stähelin *et al.*, 2023). In Bangladesh, little attention has been given to the overall impact of task characteristics, technology characteristics, institutional support, and task–technology fit.

This paper fills that gap (Rita Yuniarti *et al.*, 2025). It uses a survey-based partial least squares structural equation modelling method to study the adoption of digital health applications by community health workers (Roy, 2022). It specifically examines the three variables of task characteristics, technology characteristics and institutional support whether they enhance task technology fit. It also evaluates that task-technology fit and institutional support have a direct positive effect on the adoption of digital health applications (Roy *et al.*, 2022). Lastly, it looks at the transmission of the impact of task and technology characteristics to adoption through task- technology fit.

The research has its contribution as it incorporates the technical, occupational, and organisational explanations into a single mode (Anam Shahil-Feroz, 2021). It also offers real world experience to government agencies, non-governmental organisations, community clinics, development organisations, and digital health system designers aiming to reinforce sustainable application usage.

LITERATURE REVIEW

Digital Health Applications in Community Healthcare

Digital health application Digital health application may mean mobile health, web-based health or computer-supported health used to enhance the delivery of health services, information management, communication, monitoring, and decision making (Ramachandran *et al.*, 2025). These applications can be used to promote household registration, maternal and child health surveillance, immunisation surveillance, health education, coordination of referrals, disease reporting, and routine administration at the community level (Santos *et al.*, 2023). The local health context is such that it gives a powerful demand to digital tools (Mellinda *et al.*, 2025). Health workers can cross household boundaries, work in poorly developed areas, and work with various types of patients. They are also required to report to the supervisors and make periodic reports (Panjabi *et al.*, 2021). With a well-designed application, there are chances of minimizing redundant data entry and instant access to information when it is needed.

However, the two different outcomes are technology deployment and technology adoption (Asif Akhtar *et al.*, 2024). The introduction of a system is termed as deployment. Its acceptance, further usage and incorporation into routine activities are reflected through adoption (Lathifah *et al.*, 2023). Community health workers

can be provided with a digital application and keep using paper records. This behaviour could be realized when the application is not consistent with their activities or when institutional arrangements are insufficient.

Task Characteristics

Task characters are the nature and requirements of the tasks that the users are required to do (Akhtar *et al.*, 2025). Community health work entails collection of information, communication with patients, record keeping, referral, reporting, field-level decision making and coordination with healthcare institutions (Blondino *et al.*, 2024). These activities vary in levels of difficulty, urgency, physical location, and information level.

Certain activities are organized and monotonous. Examples are the entry of household data or documentation of regular service delivery (Islam *et al.*, 2024). Other activities involve judgement including the identification of a high-risk patient or the process of making a judgement whether a referral is needed or not. A computer program should be capable of supporting both the routine and decision-oriented processes.

Characteristics of tasks determine the kind of technology needed (Greuel *et al.*, 2023). An employee who travels to distant families might need to be able to go offline and quickly synchronise his data. A maternal health worker might be in need of pregnancy monitoring, risk notification, and referral capabilities (Santos *et al.*, 2025). Summary dashboards and automated reporting may be necessitated by a reporting officer.

The task characteristics and adoption relationship might not necessarily be direct (Haq *et al.*, 2024). Complicated jobs are not always better in utilizing the application. On the contrary, task demands bring about a necessity of suitable technological support. There is increased chances of adoption when the application available meets the need (Wasunna & Holeman, 2021). Task-technology fit thus offers the means by which task characteristics can add to adoption.

Technology Characteristics

Technology characteristics are the characteristics and performance of a digital system. They encompass usability, reliability, accessibility, information quality, processing speed, security and functional clarity (Rodrigues *et al.*, 2022). These attributes decide the ability of an application to work within the environment in which the user is working.

Community health workers of varying educational and technical backgrounds find ease of learning especially important. Complex interface can enhance errors and decrease confidence. There is also need of reliable functions since a technical failure during contact with a patient may disrupt the delivery of services (Sulyaprilawati Battri Siahaan & Marice Simarmata, 2025).

Accessibility is necessary as community health workers often work outside of formal health systems. The applications must work on the available devices as well

as in varying network environments (Zaman *et al.*, 2025). The information should be presented in a manner that is understandable. Storing data in a safe place must also be taken into account since community health records are personal data which are sensitive.

The characteristics of technology are meaningful when they relate to the real job demands (Stähelin *et al.*, 2023). An app might have numerous sophisticated functions, but the value might also be limited when it does not relate to healthcare activities in the community. The quality of technology must as such be assessed in relation to the requirement of the task quite as opposed to being an independent property (Feroz *et al.*, 2021).

Institutional Support

Institutional support is the resources, advice, motivation and help given by an organisation. It can encompass training, provision of devices, internet services, technical troubleshooting, supervisory guidance, implementation guidelines and management commitment (Rita Yuniarti *et al.*, 2025).

Adoption of digital health may necessitate organisational change. New processes are to be taught to workers. Forms of reporting can vary (Roy, 2022). There may be a transition to have paper and electronic systems operating together. Such circumstances may put extra strain on users. This pressure can be mitigated through institutional support through clarifying the expectations and offering real-world help (Roy *et al.*, 2022).

Training assists users in knowing how the applications work. Technical assistance is used to overcome operational challenges (Anam Shahil-Feroz, 2021). The provision of devices and the internet lessen individual financial liabilities. Supervisory encouragement sends the message that the use of the application is appreciated. Clear guidelines make the system not difficult to understand on how and when to use it (Ramachandran *et al.*, 2025).

Adoption can be impacted directly by institutional support. With the necessary resources and management support, workers will tend to make use of an application. Task technology fit also can be enhanced through support (Santos *et al.*, 2023). Supervision and training can assist workers to recognize the relationship between certain application functions and their duties. Thus, the role of institutional support is enabling and integrating.

Task–Technology Fit

Tasktechnology fit is the level of the correspondence between the requirements of tasks and the previous technology abilities (Mellinda *et al.*, 2025). Technology shows a high fit where the technology assists the user to perform the pertinent tasks with high accuracy, speed and efficiency.

Fit can have various manifestations in community healthcare (Panjabi *et al.*, 2021). The application could help streamline the household registration. It could give patient information in time. It can enhance referral communication. It can minimize the duplication of

reporting. It can also empower workers to accomplish anything within the process of travelling among communities (Akhtar *et al.*, 2025).

Tasktechnology fit is not the same as overall satisfaction with technology. An employee can find an application user friendly and yet find it unsuitable to perform a specific job. Likewise, an application can be highly technical and not fit the existing workflow (Lathifah *et al.*, 2023). Fit is thus concerned with the functional compatibility as opposed to general attitudes.

The good fit may enhance frequent use as it becomes a part of the routine. Employees will not consider it as an extra administrative burden (Asif Akhtar *et al.*, 2024). Rather, they view it as an instrument which assists them in fulfilling their professional duties.

Digital Health Application Adoption

Digital health application adoption can be defined as the process of acceptance, use, sustained use, and integration of an application into the regular healthcare practice (Blondino *et al.*, 2024). The adoption can be indicated by use frequency, preference towards digital systems, desire to utilize more features, and desire to remain using the application.

Adoption is behavioural and continuance aspects (Islam *et al.*, 2024). The first-use can be the one, which is necessary to the institution. Sustainable adoption emerges when the workers keep on using the system due to its ability to sustain their work (Greuel *et al.*, 2023). As such, the adoption quality cannot be measured by posing a question about the application being installed.

When it is used regularly, it means that the application is becoming operationally relevant (Santos *et al.*, 2025). Long-term intention implies that users are willing to use it in future. To the colleagues is recommended as useful. All these factors give a larger evaluation of adoption.

Research Gap

Current adoption frameworks tend to focus on the personal perceptions. The actual correspondence between the community health tasks and the functionality of digital applications receive less attention (Haq *et al.*, 2024). The analysis of institutional conditions is also not always combined with the design of technology.

This division narrows the knowledge. There is an interrelationship between the task demands, the aspects of technology, the organisational resources and the behaviour of the user (Wasunna & Holeman, 2021). These dimensions are merged into a single structural model in the current research. It looks at direct impacts on task-technology fit and adoption of application. It also verifies the hypothesis that task-technology fit is a mediator between task and technology features and adoption (Rodrigues *et al.*, 2022).

It is especially applicable to Bangladesh, where community health services are delivered in rural, urban, semi-urban/hard-to-reach contexts (Sulyaprilawati

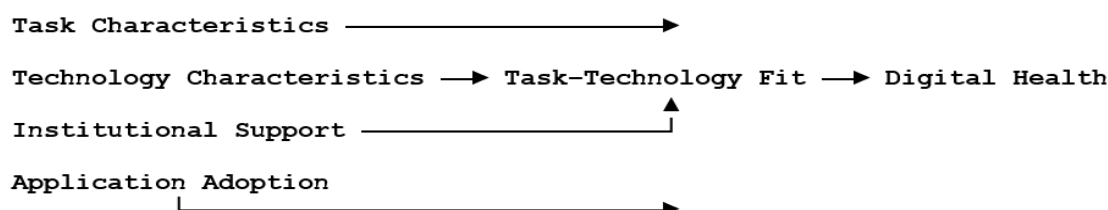
Battri Siahaan & Marice Simarmata, 2025). The community health workers can provide insight into the design and implementation of digital health systems that align with the realistic conditions of service-delivery.

Conceptual Framework and Hypotheses

Conceptual Framework

There are five reflective constructs in the conceptual model. Exogenous constructs are task characteristics, technology characteristics, and institutional support (Zaman *et al.*, 2025). A mediating construct that is endogenous is task-technology fit. The last endogenous

construct is the adoption of digital health applications. The model will assume that there is an instance of need created by task requirements (Stähelin *et al.*, 2023). The characteristics of the technology dictate whether the application available can meet such a need. Institutional support is the resources and organisational conditions needed to bridge the application to the everyday work. Task-technology fit will be assumed to be the primary functional process that results in adoption. There is also an anticipation of a direct influence by the institutional support since training, technical assistance, provision of devices, and encouragement by supervisors can influence use independently (Feroz *et al.*, 2021).



The abstracted relationships can be seen as follows:

Hypotheses

H1: Task characteristics have a positive and significant effect on task–technology fit among community health workers.

H2: Technology characteristics have a positive and significant effect on task–technology fit among community health workers.

H3: Institutional support has a positive and significant effect on task–technology fit among community health workers.

H4: Task–technology fit has a positive and significant effect on digital health application adoption.

H5: Institutional support positively and significantly influences the adoption of digital health applications.

H6: Task–technology fit positively and significantly mediates the relationship between task characteristics and digital health application adoption.

H7: Task–technology fit positively and significantly mediates the relationship between technology characteristics and digital health application adoption.

MATERIALS AND METHODS

Research Design

The research design used was quantitative and cross-sectional. The design was suitable as the study aimed at quantifying the perceptions and digital health practices among community health workers at a certain point in time (Rita Yuniarti *et al.*, 2025). It also enabled concomitant testing of the proposed relationships among several latent constructs.

A systematic survey technique was adopted. The community health worker at the individual level was the unit of analysis. The experiment targeted individuals who were practically exposed to a digital health application that they could use in their professional activities.

This research model was explanatory and predictive (Roy, 2022). The explanatory part determined the strength and significance of the offered structural relationships. The

predictive part looked into whether the model was capable of making helpful predictions in unknown observations.

Study Population and Eligibility

The group of interest was the community health workers working in Bangladesh. The respondents were representative of government healthcare institutions, non-governmental organisations, private healthcare organisations, development organisations and community clinics.

The respondents had to be in an active community-level healthcare position (Roy *et al.*, 2022). They had to have experience with using an electronic health application in professional work as well. Possible jobs were community health care providers, health assistants, family welfare assistants, community skilled birth attendants, NGO health workers, private-sector community health workers and field or outreach workers.

The last dataset consisted of 530 valid observations (Anam Shahil-Feroz, 2021). The respondents represented all the eight districts of Bangladesh. The sample included also rural, urban, semi-urban and remote or hard to reach working places.

Sampling and Data Collection

The purposive sampling method was appropriate since the research needed respondents who had firsthand experience of digital health applications. The questionnaire was sent to the workers who were in a position to assess their work loads as well as the performance of the digital systems that they applied during their work loads.

Participation was voluntary (Ramachandran *et al.*, 2025). The academic nature of the study was explained to the respondents. They were also made aware that their answers would be kept confidential. The structural analysis did not require any personally identifying information.

The survey included eligibility questions, demographic questions and measurement statements. Screening questions ensured that the respondent was already in a

professional position, had recent application experience and agreed to undergo the interview.

Questionnaire and Measurement

The measurement tool consisted of five constructs and 35 indicators. There were six questions to measure task characteristics (Santos *et al.*, 2023). There were seven items used to measure technology characteristics. Eight items were used to measure institutional support. Task-technology fit was measured with seven items. The adoption of digital health applications was assessed using seven items.

Some of the task characteristics evaluated the task requirements (information collection, reporting, coordination, decision-making and workload). Technology features evaluated usability, reliability, accessibility, quality of information, speed of response, security and functional comprehensibility.

The institutional support measured training, technical support, supervisory support, availability of devices, internet support, clear instructions, learning time, and management commitment (Mellinda *et al.*, 2025). Task-technology fit was used to evaluate the fit between work requirements and application functions. The use of digital health applications was measured in terms of regular use, integration, preference, further intention, continued use, recommendation and routine dependence.

Each construct item was rated using a five-point Likert scale. The scale was scored on a Likert scale, that is, strongly disagree to strongly agree. The increased scores were indicative of stronger perceptions of the measured construct.

PLS-SEM Procedure

Partial least squares structural equation modelling was used to evaluate the research model (Panjabi *et al.*, 2021). The PLS-SEM was suitable since the model had a variety of latent variables, direct effects, indirect effects and prediction-based goals. It also allowed the concomitant measurement of quality of measures and structural relationships.

The two-stage analysis was performed. The measurement model was tested in the first stage. Outer loadings were used as an indicator of reliability. Cronbach alpha and composite reliability were used as the measure of internal consistency. Average variance extracted was used to measure convergent validity.

Fornell-Larcker criterion and Heterotrait-monotrait ratio were the measures which were used to ascertain discriminant validity. Indicators with a loading more than 0.708 were considered to be satisfactory (Lathifah *et al.*, 2023). The coefficients of reliability were deemed to be acceptable in the range of 0.70. AVE the greater than 0.50 favored convergent validity. A value of less than 0.85 of the HTMT was an indication of discriminant validity.

The second phase considered the structural model. The

factors of variable inflation were checked at the inner variance and subsequently the path coefficients were interpreted. The model power was measured using the coefficients of determination. Effects sizes were evaluated to identify the personal contribution of each of the predictors.

Standard errors, t-statistic, p-values, and percentile confidence intervals were obtained by means of nonparametric bootstrapping (Akhtar *et al.*, 2025). When the coefficient was positive as was expected, the p-value was less than 0.05 and the interval did not include zero, the hypothesis was considered supported.

Indirect effects were used to assess mediation. The mediating effects between task characteristics and technology characteristics to adoption were directly tested and estimated with the help of task-technology fit.

Common Method Bias and Collinearity

Due to the selection of the predictor and outcome data using the same questionnaire, common method bias was evaluated (Asif Akhtar *et al.*, 2024). A single factor test by Harman was used as a preliminary diagnostic. A percentage of less than 50 percent in the first-factor meant that there was no one factor that dominated the measurement variance.

Also looked at were full collinearity VIF values. The values were lower than 3.30 meaning that vertical and lateral collinearity is not a significant issue (Blondino *et al.*, 2024). This methodology offered a more robust evaluation in comparison to solely depending on the Harman test.

Model Fit and Predictive Assessment

SRMR, RMSEA, CFI, NFI, IFI, NNFI, GFI and RMS theta were used to assess the model fit. These measures were considered to be secondary evidence since the main focus of the PLS-SEM was on explanation and prediction.

A ten-fold procedure was used to evaluate out-of-sample prediction. The number of training observations was 477 and the number of observations used in the test was 53 observations in a single fold-based testing (Islam *et al.*, 2024). A benchmarking of PLS prediction errors against a linear-model benchmark was made.

Q 2 predict assessed predictive relevance. Positive values meant that the model was better than a naive prediction by the mean. There were also a comparison of MAE and RMSE values with the benchmark. Compromised PLS errors showed better predictive performances.

RESULTS AND DISCUSSION

Respondent Profile

The biggest gender group was female respondents. There were 303 female participants (57.17) and 219 male participants (41.32). Three respondents were in a different gender and five could not indicate their gender. The majority was thus composed of women.

Table 1: Demographic and Professional Profile of Respondents

Variable	Category	Frequency	Percentage
Gender	Male	219	41.32
	Female	303	57.17
	Other	3	0.57
	Prefer not to disclose	5	0.94
Age group	Below 25 years	34	6.42
	25–34 years	178	33.58
	35–44 years	202	38.11
	45–54 years	99	18.68
	55 years or above	17	3.21
Education	SSC or equivalent	38	7.17
	HSC or equivalent	174	32.83
	Diploma or professional certificate	150	28.30
	Bachelor's degree	137	25.85
	Master's degree or above	21	3.96
	Other	10	1.89
Professional position	Community Health Care Provider	115	21.70
	Health Assistant	105	19.81
	Family Welfare Assistant	110	20.75
	Community Skilled Birth Attendant	53	10.00
	NGO/private-sector community health worker	72	13.58
	Field or outreach worker	63	11.89
	Other	12	2.26
Institution	Government healthcare institution	266	50.19
	Non-governmental organisation	126	23.77
	Private healthcare organisation	43	8.11
	Development organisation	29	5.47
	Community clinic	58	10.94
	Other	8	1.51
Experience	Less than 1 year	35	6.60
	1–3 years	118	22.26
	4–6 years	149	28.11
	7–10 years	132	24.91
	More than 10 years	96	18.11
Work location	Rural area	306	57.74
	Urban area	94	17.74
	Semi-urban area	86	16.23
	Remote or hard-to-reach area	44	8.30
Division	Barishal	34	6.42
	Chattogram	94	17.74
	Dhaka	144	27.17
	Khulna	59	11.13
	Mymensingh	31	5.85
	Rajshahi	54	10.19
	Rangpur	64	12.08
	Sylhet	50	9.43

Device	Personal smartphone	143	26.98
	Institution-provided smartphone	205	38.68
	Tablet	73	13.77
	Laptop or desktop	29	5.47
	More than one device	75	14.15
	Other	5	0.94
Application experience	Less than 6 months	52	9.81
	6 months to 1 year	125	23.58
	More than 1–3 years	193	36.42
	More than 3–5 years	110	20.75
	More than 5 years	50	9.43
Use frequency	Less than once a week	25	4.72
	One or two days per week	60	11.32
	Three or four days per week	135	25.47
	Five or six days per week	140	26.42
	Every day	170	32.08
Formal training	Yes	403	76.04
	No	127	23.96

The biggest age group was 3544 years, which included 202 respondents or 38.11% of the sample.

Ages 25-34 years had 33.58% of the participants and ages 45-54 years had 18.68% of the respondents. Only 6.42% were below 25 years and 3.21% were aged 55 years or above.

The highest educational group was found to be the respondents with HSC or equivalent at 32.83%. A holder of diploma or professional certificate was 28.30, with a bachelor degree holder being 25.85. Smaller percentages were educated to SSC-level, had a master degree or higher degree or other.

The greatest occupation group was Community Health Care Providers with 21.70. The percentage of Family Welfare Assistants and Health Assistants were 20.75 and 19.81, respectively. There were also NGO or community health workers in the private sector or field or outreach workers and Community Skilled Birth Attendants.

In government healthcare organizations 50.19% of the respondents were employed. There was a total of 23.77 non-governmental organisations and the rest of the percentage was comprised of community clinics, private healthcare organisations, development organisations and other institutions. The sample thus was both public and non-public.

The highest percentage was 28.11% of the respondents who were four to six years old. Individuals who had between seven to ten years' experience constituted 24.91, with 22.26 experiencing between one to three years. Another 18.11% were over ten years experienced. The sample is composed of 57.74% rural workers. The proportion of urban and semi-urban respondents was 17.74% and 16.23, respectively, and 8.30% lived in remote or hard-to-reach locations. The clear majority was thus rural respondents.

There was representation of all the eight administrative divisions. Dhaka made the highest contribution of 27.17 and Chattogram made 17.74. There was a wide geographical coverage with Rangpur, Khulna, Rajshahi, Sylhet, Barishal and Mymensingh also providing respondents.

The most commonly used devices were those provided by the institution, with 38.68% of the respondents reporting using the smartphones. Personal phone 26.98. Mobile devices such as tablets, use of multiple devices, laptops or desktop computers as well as other gadgets were smaller proportions. The main access medium was the Smartphones.

The highest percentage (36.42) was obtained in the category of over a year and less than three years of application experience. The respondents who had between six months to one year were 23.58 and those who had over three to five years' experience was 20.75. With the majority, they were well exposed in a practical manner.

The highest category was 32.08 comprised of daily users. A 26.42% of the respondents used digital health applications five or six days a week, and 25.47% used it three or four days a week. The applications were thus often incorporated into everyday work.

Majority of the respondents were formally trained. Of the total of 403 respondents who gave the response, 76.04% indicated that they had formal preparation, with 23.96% indicating a lack of formal preparation. Training was fair in institutions, however, there were a significant number who were untrained.

Common Method Bias

The initial factor had 36.086% of the total variance. This was less than the 50 percent mark. The test of Harman thus revealed that there was no common factor that was overriding.

Table 2: Common Method Bias and Full Collinearity Assessment

Assessment	Construct/Result	Value	Threshold	Decision
Harman's single-factor test	First-factor variance	36.086%	Below 50%	Acceptable
Full collinearity VIF	TAC	1.147	Below 3.30	Acceptable
	TEC	1.443	Below 3.30	Acceptable
	INS	1.405	Below 3.30	Acceptable
	TTF	2.403	Below 3.30	Acceptable
	DHA	1.934	Below 3.30	Acceptable

Note: TAC = Task Characteristics; TEC = Technology Characteristics; INS = Institutional Support; TTF = Task-Technology Fit; DHA = Digital Health Application Adoption.

The entire values of VIF of collinearity were between 1.147 and 2.403.

The entire values were less than 3.30. The cumulative evidence indicated that a common method bias was not a critical factor to interpretation of the structural

relationships (Greuel *et al.*, 2023).

Indicator Reliability

Measurement items were all above the recommended loading of around 0.708. TEC6 had the lowest loading of

Table 3: Outer Loadings

Construct	Indicator	Loading	Construct	Indicator	Loading
Task Characteristics	TAC1	0.840	INS	INS4	0.833
	TAC2	0.832	INS	INS5	0.789
	TAC3	0.829	INS	INS6	0.823
	TAC4	0.802	INS	INS7	0.832
	TAC5	0.787	INS	INS8	0.812
	TAC6	0.833	TTF	TTF1	0.867
Technology Characteristics	TEC1	0.824	TTF	TTF2	0.874
	TEC2	0.834	TTF	TTF3	0.838
	TEC3	0.859	TTF	TTF4	0.870
	TEC4	0.809	TTF	TTF5	0.836
	TEC5	0.833	TTF	TTF6	0.816
	TEC6	0.730	TTF	TTF7	0.858
	TEC7	0.825	DHA	DHA1	0.867
Institutional Support	INS1	0.854	DHA	DHA2	0.857
	INS2	0.832	DHA	DHA3	0.834
	INS3	0.823	DHA	DHA4	0.883
			DHA	DHA5	0.806
			DHA	DHA6	0.788
			DHA	DHA7	0.841

Note: TAC = Task Characteristics; TEC = Technology Characteristics; INS = Institutional Support; TTF = Task-Technology Fit; DHA = Digital Health Application Adoption.

0.730. The greatest loading was 0.883 with DHA4. Not a single indicator needed to be removed.

The TAC loadings ranged from 0.787 to 0.840. TEC loadings ranged from 0.730 to 0.859. INS loadings ranged from 0.789 to 0.854. TTF loadings ranged from 0.816 to 0.874. DHA loadings ranged from 0.788 to 0.883. These findings were able to anchor indicator reliability.

Reliability and Convergent Validity

The alpha values of Cronbach were between 0.903 and 0.937. The values of composite reliability were between 0.925 and 0.949. The values were all over 0.70 and lower

than the traditional upper level of 0.95. The constructs thus proved a good internal consistency with no clear signs of over redundancy of items.

The AVE values ranged from 0.668 to 0.725. Every value exceeded 0.50. The corresponding construct thus explained more than half of the indicator variance. Convergent validity was achieved.

The estimates of rho A were 1.000. Since this was an upper-bound estimate, reliability conclusions were made based on a combination of Cronbach (alpha), composite (rho) and item (loading) and AVE as opposed to a combination of rho A alone.

Table 4: Construct Reliability and Convergent Validity

Construct	Cronbach's Alpha	rho_A	Composite Reliability	AVE
Task Characteristics	0.903	1.000	0.925	0.673
Technology Characteristics	0.917	1.000	0.933	0.668
Institutional Support	0.933	1.000	0.944	0.680
Task–Technology Fit	0.937	1.000	0.949	0.725
Digital Health Application Adoption	0.930	1.000	0.944	0.706

Discriminant Validity

Square root of AVE of each construct exceeded correlations

of construct with the rest of constructs.

Technology characteristics had the lowest diagonal of 0.817.

Table 5: Fornell–Larcker Criterion

Construct	TAC	TEC	INS	TTF	DHA
TAC	0.821				
TEC	0.154	0.817			
INS	0.168	0.253	0.825		
TTF	0.353	0.552	0.452	0.852	
DHA	0.265	0.325	0.515	0.649	0.840

Note: Bold diagonal values are the square roots of AVE.

Note: TAC = Task Characteristics; TEC = Technology Characteristics; INS = Institutional Support; TTF = Task–Technology Fit; DHA = Digital Health Application Adoption.

Task-technology fit to digital health application adoption had the highest inter-construct correlation of 0.649.

These findings showed that the constructs had more

variance with their indicators compared to other constructs (Santos *et al.*, 2025). The FornellLarcker criterion was so met.

Table 6: Heterotrait–Monotrait Ratio

Construct	TAC	TEC	INS	TTF	DHA
TAC	1.000				
TEC	0.168	1.000			
INS	0.181	0.272	1.000		
TTF	0.383	0.594	0.483	1.000	
DHA	0.289	0.349	0.551	0.693	1.000

Note: TAC = Task Characteristics; TEC = Technology Characteristics; INS = Institutional Support; TTF = Task–Technology Fit; DHA = Digital Health Application Adoption.

There was a value of all HTMT less than 0.85. Values ranged from 0.168 to 0.693. The maximum HTMT value was noted among tasktechnology fitness and adoption of digital health applications.

The values supported the fact that the five constructs were empirically different. The FornellLarcker as well

as the HTMT assessments thus supported discriminant validity.

Structural Collinearity and Model Fit

The value of all the inner VIFs was significantly smaller than the conservative value of 3.00. The estimates of

Table 7: Structural Collinearity and Model Fit

Assessment	Relationship/Index	Value
Inner VIF	TAC → TTF	1.043
	TEC → TTF	1.083
	INS → TTF	1.088
	INS → DHA	1.257
	TTF → DHA	1.257
Model fit	SRMR	0.035
	RMSEA	0.027
	RMS theta	0.025
	CFI	0.983

	IFI	0.983
	NFI	0.943
	NNFI	0.982
	GFI	0.866
	Chi-square	770.316
	Degrees of freedom	552

Note: TAC = Task Characteristics; TEC = Technology Characteristics; INS = Institutional Support; TTF = Task–Technology Fit; DHA = Digital Health Application Adoption.

the structural coefficients were not distorted due to multicollinearity.

The SRMR was 0.035 and RMSEA was 0.027. The two values showed a minor difference between the model implied and empirical relationship. The values of CFI and IFI as well as NFI and NNFI also depicted reasonable

model fit. These fit indices presented additional evidence in support of the given model.

Explanatory Power and Effect Sizes

The factors together that explained 46.2% of the variance in task-technology fit were task characteristics, technology

Table 8: Coefficients of Determination and Effect Sizes.

Endogenous Construct	R ²	Adjusted R ²	Predictor	f ²	Magnitude
TTF	0.462	0.459	TAC	0.098	Small
			TEC	0.331	Medium-to-large
			INS	0.155	Medium
DHA	0.482	0.480	INS	0.119	Small-to-medium
			TTF	0.420	Large

Note: TAC = Task Characteristics; TEC = Technology Characteristics; INS = Institutional Support; TTF = Task–Technology Fit; DHA = Digital Health Application Adoption.

characteristics, and institutional support. This value was adjusted to 45.9%. The model hence showed a moderate explanatory capability of task technology fit.

Institutional support and task–technology fit explained 48.2% of the variance in digital health application adoption. The value was adjusted down to 48.0%. This showed a moderate and steady performance in terms of explanation.

The largest contribution to task technology fit was

the characteristics of technology with an f^2 of 0.331. The medium-effect of institutional support on task technology fit was medium. Characteristics of tasks had a lesser effect (Haq *et al.*, 2024). Task-technology fit had an immense impact on application adoption.

Direct Effects and Hypothesis Testing

Task characteristics had a positive effect on task–technology fit. H1 was supported. This finding showed

Table 9: Direct Structural Relationships.

Hypothesis	Relationship	β	SE	t-value	p-value	95% CI	Decision
H1	TAC → TTF	0.234	0.033	7.164	<0.001	[0.172, 0.301]	Supported
H2	TEC → TTF	0.440	0.032	13.837	<0.001	[0.377, 0.501]	Supported
H3	INS → TTF	0.301	0.032	9.522	<0.001	[0.240, 0.363]	Supported
H4	TTF → DHA	0.523	0.032	16.122	<0.001	[0.457, 0.584]	Supported
H5	INS → DHA	0.278	0.034	8.303	<0.001	[0.214, 0.345]	Supported

Note: TAC = Task Characteristics; TEC = Technology Characteristics; INS = Institutional Support; TTF = Task–Technology Fit; DHA = Digital Health Application Adoption.

that the perceived relevance of digital applications was contributed by the nature and information needs of community health work.

The highest impact on task-technology fit was on technology characteristics. H2 was supported. The availability of information, security, usability, reliability, and accessibility were key elements in ensuring a good fit between technology and work.

Institutional support had a positive effect on task–technology fit. H3 was supported. The organisational

resources and advice assisted the workers to absorb application capabilities into their tasks.

The best direct predictor of adoption of digital health applications was task-technology fit. H4 was supported (Wasunna & Holeman, 2021). There was also a major direct impact of institutional support. H5 was hence supported.

Indirect and Total Effects

The task-technology fit on adoption was positive and

significant indirectly influenced by the characteristics of the task. The zero was not contained in the confidence

Table 10: Indirect and Total Effects on Digital Health Application Adoption

Hypothesis/Effect	Indirect Effect	SE	t-value	p-value	95% CI	Total Effect	Decision
H6: TAC → TTF → DHA	0.123	0.019	6.295	<0.001	[0.086, 0.164]	0.123	Supported
H7: TEC → TTF → DHA	0.230	0.022	10.547	<0.001	[0.189, 0.274]	0.230	Supported
INS → TTF → DHA	0.158	0.019	8.468	<0.001	[0.123, 0.196]	0.436	Significant

Note: TAC = Task Characteristics; TEC = Technology Characteristics; INS = Institutional Support; TTF = Task–Technology Fit; DHA = Digital Health Application Adoption.

interval. H6 was supported.

There was also an indirect impact of technology characteristics. It was larger than the indirect influence of the task characteristics. H7 was supported. The outcome validated that quality of technology facilitated its adoption mainly by enhancing its alignment with the work demands.

Through task technology fit, institutional support resulted

in a direct as well as an indirect impact. It had a net impact of 0.436. The institutional support thus contributed to adoption in multiple ways.

Predictive Assessment

There were no negative values in Q2 predict. They ranged from 0.274 to 0.385. The model thus was predictively relevant in all task technology fit and adoption indicators.

Table 11: PLS predict Results.

Indicator	MAE PLS	MAE Benchmark	RMSE PLS	RMSE Benchmark	Q ² _predict
TTF1	0.839	0.852	1.031	1.055	0.328
TTF2	0.844	0.851	1.021	1.042	0.315
TTF3	0.829	0.847	1.018	1.047	0.328
TTF4	0.825	0.846	1.013	1.045	0.337
TTF5	0.905	0.924	1.100	1.121	0.299
TTF6	0.847	0.867	1.012	1.037	0.330
TTF7	0.833	0.854	1.018	1.041	0.356
DHA1	0.849	0.958	1.029	1.151	0.363
DHA2	0.870	0.941	1.061	1.154	0.320
DHA3	0.828	0.923	1.010	1.121	0.356
DHA4	0.812	0.923	0.998	1.133	0.385
DHA5	0.829	0.926	1.016	1.138	0.303
DHA6	0.880	0.965	1.056	1.169	0.274
DHA7	0.843	0.940	1.016	1.137	0.356

Note: TAC = Task Characteristics; TEC = Technology Characteristics; INS = Institutional Support; TTF = Task–Technology Fit; DHA = Digital Health Application Adoption.

All 14 indicators had lower MAE and RMSE values in the PLS model, compared to the linear benchmark. Task-technology fit and digital health application adoption had average values of Q2 predict 0.328 and 0.337, respectively. Both the positive Q2 predict value and the reduction in the prediction error showed good out samples predictive performance (Rodrigues *et al.*, 2022). The model was thus effective in the prediction and explanation.

Discussion

The results indicate that the implementation of digital health applications among community health workers is heavily determined by the connection between technology and work. The direct predictor of adoption with the greatest impact was task-technology fit. This finding indicates that application adoption amongst workers does not occur due to its availability or institutional mandate

(Sulyaprilawati Battri Siahaan & Marice Simarmata, 2025). When applications are useful to their duties, they are bound to involve them in normal work.

Technology characteristics had the strongest effect on task–technology fit. This means that the quality of applications is the key to implementation in digital health. Systems need to be dependable, available, comprehensible, and able to relay pertinent information (Zaman *et al.*, 2025). Devices and training, offered as part of a digital health programme may not take off when the application itself is not very good.

The presence of relatively strong influence of technology characteristics also indicates the field-based nature of community healthcare (Stähelin *et al.*, 2023). Applications that should be utilized when workers make house calls and community outreach should be provided. Direct interference with service delivery can be realized through

slow processing, poorly defined roles, incompetent management of connections or unreliable information (Feroz *et al.*, 2021). The real field conditions should therefore form the basis of technical design.

Task characteristics also had a positive effect on task-technology fit. Community health workers found greater fit between application functions and data collection, reporting, coordination, decision-making and workload

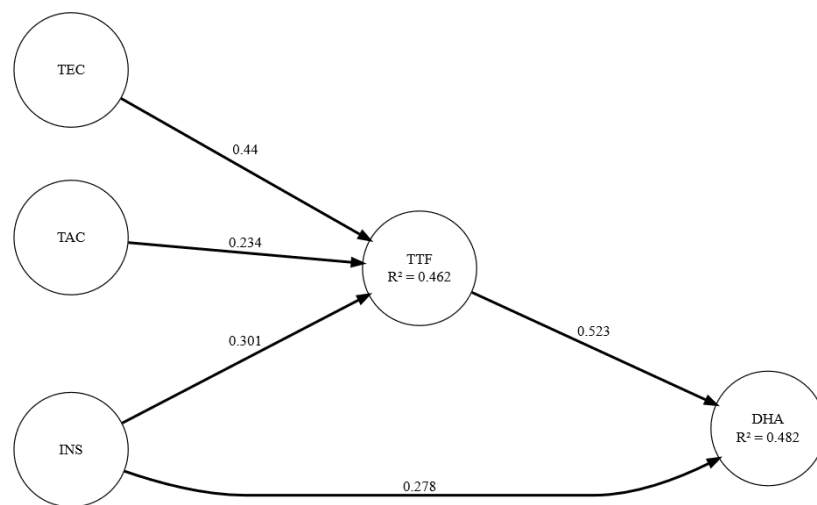


Figure 1: SEM Structural Model of the Study.

Note: TAC = Task Characteristics; TEC = Technology Characteristics; INS = Institutional Support; TTF = Task-Technology Fit; DHA = Digital Health Application Adoption.

needs (Rita Yuniarti *et al.*, 2025). The impact was less than impact of the technology characteristics, but still statistically and practically significant.

The finding implies that the design of the application must start by a close study of the health tasks in the community. The developers would have to study what information the workers gather, when they require it, how they communicate and where delays exist (Roy, 2022). The workflows should then be configured around technology. Both task and technology fit and adoption were influenced by institutional support. Its direct influence on adoption proved that workers need more than an application appropriate. They should, as well, be trained, provided with technical support, equipment, Internet access, focused instructions, and administrative motivation.

The indirect impact of institutional support further indicated that organisations aid the workers in linking the application with their responsibilities (Anam Shahil-Feroz, 2021). Training can be used to elaborate on how a given reporting need can be enabled by a given functional role. Supervision can help motivate workers to utilize digital records when in the field. Technical support can help in avoiding the short-term operational issues in the long term.

The overall impact of institution support was enormous. This observation makes institutions active agents of implementation as opposed to technology providers. An introduction of an application should not be ended with management commitment (Roy *et al.*, 2022). It takes a continuous support, surveillance, and adjustment to sustainable adoption.

The results of the mediation shed some more light. Task characteristics had an effect on adoption with task-technology fit. This implies that the information-

intensive tasks or demanding work is not necessarily the result of the use of a digital application (Ramachandran *et al.*, 2025). The employee has to feel that application will fit the tasks.

Technology characteristics also brought about adoption in task technology fit. This indirect effect was more powerful compared to the indirect effect of task characteristics (Santos *et al.*, 2023). Quality technology thus promotes change since it provides a working fit with work tasks.

Both endogenous constructs had a moderate explanatory power in the model. Almost 50 percent of the difference in task and technology fit and adoption was explained (Mellinda *et al.*, 2025). The level holds some significance since personal confidence, digital literacy, social influence, workload, infrastructure quality and policy requirements can also be significant factors affecting digital health behaviour.

The findings are reinforced by the predictive results. The model yielded positive predictive relevance on all the target indicators. It additionally performed higher on all MAE and RMSE checks when compared to the linear benchmark (Panjabi *et al.*, 2021). The model thus did not just describe associations in the sample of estimation. It also showed a capability to forecast for observations not in the model-training process.

Theoretical and Practical Implications

Theoretical Implications

The research goes beyond the existing studies on digital health adoption by making the task-technology fit central to the process of adoption. It demonstrates that only general attitudes towards technology should not be used to explain adoption (Lathifah *et al.*, 2023). There

must be functional overlap between the capabilities of applications and the job requirements.

Another element that is incorporated in the task-technology fit model is the institutional support. Both fit and adoption were impacted by institutional support (Akhtar *et al.*, 2025). This observation demonstrates that fit is not developed just by technical design. Training, supervision, resources, and implementation guidance can also be of help in strengthening it.

The strong indirect associations explain the influence of task and technology features on adoption. They worked by impacting task-technology fit. The results are thus favourable of an explanation of digital health application use in terms of mechanisms.

Practical Implications

Task assessments should be done by digital health programme managers prior to the choice or creation of applications (Asif Akhtar *et al.*, 2024). The evaluation must determine reporting requirements, holding communications with patients, referral requirements, field conditions, information demands and workflow issues.

The designers of technology must focus on reliability, accessibility, relevance of information, security and easy functions. The applications must be able to run on the devices that are accessible to health workers in the community (Blondino *et al.*, 2024). The ability to operate offline and effective synchronisation can be of special significance in remote and rural locations.

Initial training and periodic refresher training should be given in institutions. Technical assistance should be readily available. Employees are not supposed to use personal gadgets or personal mobile data unless there is an explicit support set up.

Application use should be monitored constructively by the supervisors. Monitoring must help to detect workflow issues, not just impose compliance (Islam *et al.*, 2024). System updates should take into account user feedback. Community health workers must be viewed as the agents of digital health design and implementation.

Limitations and Future Research

This work was cross-sectional. It thus elicited perceptions and adoption behaviour at a point of time. Longitudinal study may be used to look at the changes in adoption following training, upgrades or longer usage of the system.

The study depended on self-reports that were made in a survey (Greuel *et al.*, 2023). In the future research, survey data can be used in conjunction with application logs, frequency of logs, time required to complete tasks, error rate, and service results.

The model looked at the task, technology and institutional factors. Future studies might involve digital self-efficacy, resistance to change, social influencing factors, workload pressure, quality of the network and data privacy issues and perceived patient benefit (Santos *et al.*, 2025).

These comparative studies may be on differences of

government and non-government workers, trained and untrained users, rural and urban workers or by type of digital health application.

CONCLUSION

This was a cross-sectional study of the uptake of digital health applications among 530 community health workers in Bangladesh. The model revealed good measurement quality, fair model fit, average explanatory power, and significant predictive accomplishment.

Task characteristics, technology characteristics and institutional support had a significant impact on task-technology fit. Task-technology fit and institutional support significantly increased digital health application adoption. All the seven hypotheses proposed were supported.

Task-technology fit was the strongest direct predictor of adoption. The most predictive predictor of fit was technology characteristics. The effect of institutional support on adoption was either direct, or indirect.

The results demonstrate that to be successful in digital health implementation, there should be alignment between work requirements, technological capabilities and organisational support. It is not adequate to have an application. The application should be aligned to community health activities, it should be reliable in the field and must be underpinned by training, resources, supervision and technical support.

The further utilization of digital health applications can be enhanced with the help of a coordinated strategy in designing technologies and implementing it on the institutional level. It is also capable of enhancing the information management and community-based healthcare delivery in Bangladesh.

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