American Journal of Smart Technology and Solutions (AJSTS)

ISSN: 2837-0295 (ONLINE)

VOLUME 5 ISSUE 2 (2026)



PUBLISHED BY
E-PALLI PUBLISHERS, DELAWARE, USA

American Journal of Smart Technology and Solutions (AJSTS)

Volume 5 Issue 2, Year 2026
ISSN: 2837-0295 (Online)
DOI: https://doi.org/10.54536/ajsts.v5i2.9024
https://journals.e-palli.com/home/index.php/ajsts

Patients' Awareness of Artificial Intelligence and Willingness to Accept AI-Assisted Medical Diagnosis in Bangladesh

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Article Information

Received: August 22, 2026

Accepted: November 12, 2026

Published: November 27, 2026

Keywords

Artificial Intelligence Awareness, Medical Diagnosis, Patient Acceptance, Perceived Diagnostic Risk, Perceived Usefulness, PLS SEM, Trust

ABSTRACT

Educating patients about AI is crucial for their acceptance of AI assisted diagnosis, assessing its utility, building trust in AI diagnostics, and recognizing potential risks. In this study, the relationships between the awareness of artificial intelligence, the perceived usefulness of the artificial intelligence, the trust in the artificial intelligence, the perceived diagnostic risk and the acceptance in the doctor supervised diagnostic setting were examined. The quantitative unit of analysis was based on 390 complete records of questionnaires with 20 indicators measured by five reflective constructs. Standard partial least squares structural equation modelling with Mode A weights was used and 10,000 bootstrap resamples were used for statistical inferences. Each construct obtained good internal consistency, convergent validity, and discriminant validity. There was a positive association between awareness and perceived usefulness ($\beta = 0.410$), trust ($\beta = 0.424$) and acceptance ($\beta = 0.190$). Perceived usefulness ($\beta = 0.261$) and trust ($\beta = 0.347$) had positive relationship with the acceptance, while perceived diagnostic risk had negative relationship with acceptance ($\beta = -0.256$). All direct relationships were significant at $p < 0.001$. Awareness also also showed significant indirect relationships with acceptance ($\beta = 0.107$) and trust ($\beta = 0.147$). The model accounted for 41.0% of the variance for acceptance. The repeated cross validation yielded a positive predictive relevance for all the values of the indicator of acceptance and lower RMSEs than those of the linear benchmark. The results highlight the need for an understanding of four unique factors that need to be considered when dealing with the acceptance of doctor supervised AIs: trust, perceived usefulness, awareness, and diagnostic risk. Information to patients should include an overview of the role of diagnostic support, maintenance of clear clinical responsibility and consideration of any concerns relating to error and future management.

INTRODUCTION

Medical diagnosis with the help of artificial intelligence creates a unique patient/clinician/computational interaction. In this context, software is used to process medical data and provide insights that can aid in diagnosis. Patients are exposed to the technology as decisions are made regarding their own care, and the significance of technology as an additional diagnostic tool goes beyond the technology itself (Osman Ali & Ahmad, 2025). They will have to ask themselves if help is welcome and if the results are worth trusting and if they are collaborating with help brings up question of their health. It is important to consider these factors in order to make sense of acceptance at the individual level where a diagnostic option becomes personally relevant.

The acceptance in this study is related to willingness to receive diagnosis with the assistance of AI under the supervision of a physician. The doctor takes the results along with other medical information, and decides on the diagnosis (Zallipalli *et al.*, 2026). It is an artificial intelligence set-up in an already established clinical relationship. Assistance thus becomes part of professional care and is not a stand-alone substitute for clinical judgement, and this is how patients assess it. The difference influences the interpretation of usefulness, trust, and risk, as each judgement relates to a particular division of responsibility between system and doctor.

Awareness is an important initial step in this evaluation (Sridhar, 2025). By providing a basic understanding of the concepts of AI-assisted diagnosis, patients can better recognize the role and scope of this technology in the diagnostic process. Familiarity could create a foundation for judging an option which may seem abstract or out of your comfort zone. But awareness is not congruent with approval. Diagnostic assistance can be understood without the immediate acceptance of the patient (Uthra Sridhar, 2025). These evaluations and the relationship between awareness and acceptance therefore needs to be explored in conjunction with the evaluations in which the awareness has relevance to a care decision.

Perceived usefulness is the expected usefulness of AAI in the diagnosis of patients. Relevant expectations encompass enhanced diagnostic accuracy, earlier detection of a health issue, more effective diagnostic decisions, and overall usefulness (Mishra, 2024). These expectations relate the technology opportunity with outcomes relevant to the patient. Even if the computational methods are not understood in detail, a patient is willing to accept additional assistance if it seems to be able to improve the process of understanding a health problem.

Trust relates to the confidence in the reliability and dependability of the diagnostic support. In a healthcare situation, person's readiness to use support may not be the same as their grasping of potential benefits of

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support (Correa *et al.*, 2026). Even if a system can be of some value, there may be a zone of uncertainty for a patient that the information gleaned from the system is reliable. On the other hand, a patient might feel that the system is reliable but for a specific diagnostic visit they do not perceive much added value (Hossain *et al.*, 2025). The combination of usefulness and trust enables these separate considerations to be examined in the context of one explanatory model.

Perceived diagnostic risk is defined as concern over the possible harm and inadequate follow-up treatment, as well as the missed chance for illness and wrong diagnosis (Shi *et al.*, 2026). These concerns are clearly linked to the impact of diagnostic judgement. Their presence makes clear that the concept of acceptance includes an evaluation of the expected positive consequences as well as the expected negative consequences (Duplaga, 2026). The model therefore acknowledges that an evaluation of usefulness can go along with an evaluation of error. The combination needs to be addressed in clinical communication because a patient's decision may be based on the understanding of the combined benefits and risks. The present study is an attempt to build an integrated account of the above said relationships (Chaturvedi, 2025). Awareness comes before perceived usefulness, trust and acceptance. Additionally, there is a direct relationship between perceived usefulness and acceptance as well as between trust and acceptance. Diagnostic risk is put forth as a separate determinant of acceptance (Hswen *et al.*, 2024). In this way it allows for testing of whether awareness is linked with acceptance beyond patients' assessments of benefit and reliability, and if so, whether it is diagnostic concern alone which contributes. The study has three aims. First, it determines if the measurement structure can be distinguished between awareness, usefulness, trust, risk and acceptance. Second, it analyses six direct relations and two indirect relations defined in the conceptual framework (Kavitha *et al.*, 2025). Third, it assesses the explanatory power of the model and its predictive power of the acceptance indicators in observations that were held out. These goals link concept understanding, statistical inference and predictive evaluation in a single analytical way.

LITERATURE REVIEW

Patient Acceptance of Artificial Intelligence Assisted Diagnosis

Technology acceptance is an evaluation process in which people are willing to accept and use a technological service (Antes *et al.*, 2021). In diagnostic care, it is the patient who is assessing the incorporation of the computer in to a clinical relationship. The patient does not have to use the system to make a meaningful acceptance decision. Their willingness refers to whether the support is used to gain understanding of their health issue as a whole with the oversight of the doctor who makes the final diagnosis (Oleribe *et al.*, 2025).

Acceptance was defined with four elements: willingness to accept assisted diagnosis, willingness to select the assistance if offered, willingness to agree on the doctor's use of the system, and willingness to accept similar assistance in future care. These indicators are different forms of behavioural intention (Seitenov *et al.*, 2026). They link immediate acceptance with a broader orientation towards participation for future diagnostics. Their common focus is the patient's willingness within a described clinical arrangement, with a coherent outcome with respect to the examination of awareness and evaluative beliefs (Augustine *et al.*, 2024).

These judgements are made with reference to a common experience, the doctor supervised scenario. The system provides suggestions and the doctor takes into account these suggestions along with other relevant information and takes the ultimate decision on diagnostics (Zhu *et al.*, 2026). This presentation frames an object for evaluation by the patients. It also helps to prevent an undifferentiated attitude towards all applications of AI from becoming consolidated as acceptance. In the current context willingness means willingness to give clinical support and is related to the professional interpretation of diagnostic information (Schaffernak *et al.*, 2026).

Artificial Intelligence Awareness and Perceived Usefulness

Artificial intelligence awareness is defined as previous acquaintance with the concept of AI, its fundamental function, and the function of assistive computational tools in medical diagnosis (Foresman *et al.*, 2024). Some of the concepts included are the purpose of a diagnostic system and how it can help a doctor. These are the elements that give a basis for understanding the clinical scenario (Phelps *et al.*, 2026). Awareness is thus considered as relevant knowledge or familiarity and not as technical skills or as proficiency in calculation techniques. The conceptual connection between awareness and usefulness comes from the action of understanding in the process of benefit evaluation (Osnat, 2025). If a system is viewed as analyzing diagnostic data and aiding in clinical decision making, patients can relate its purpose to how they believe the data should be accurate, timely, and the decision of high quality. Benefits can be made more tangible when a better understanding of the support role is provided (Baghdadi *et al.*, 2024). The positive relationship that the model posits is not an assumption about the automaticity of positive judgement based on greater familiarity per se, but rather of greater usefulness. The usefulness and value also rely on how relevant the benefit you are expecting is to you personally (Karger, 2026). Generalizations such as "this technology is cutting-edge" might have less meaning than an explanation of how the technology's discoveries might help with a patient's health issue. Awareness is the conceptual language to interpret that explanation (Jeyakumar *et al.*, 2022). Based on this, H1 is proposed that: Artificial Intelligence awareness has a positive relationship with the Perceived Usefulness of Artificial Intelligence Assisted

Medical Diagnostic systems.

Artificial Intelligence Awareness and Trust

Trust refers to the belief in the reliability of the system to provide diagnostic assistance (Baikadolla, 2025). By means of this evaluation, patients can assess this confidence on the side of a described task, the role attributed to the system and in relation to the assessment of the doctor's judgement (Westerbeek *et al.*, 2026). The trust construct does not involve an expectation of infallibility for a system. It relates to the perceived reliability of the support function of the diagnosis that is provided to respondents. This task specific interpretation is especially suited when the technology is adding information to a clinician's decision (Hemphill *et al.*, 2023).

Awareness can be linked to trust, since if a system is known to work, then patients will have a more interpretable basis for assessing their trust (Wewetzer *et al.*, 2026). A medical decision, made by a machine, could be easily gauged as a defined support role. Familiarity can also serve to highlight the ongoing need for clinical interpretation. These considerations give a theoretical foundation for the predicted increase in awareness that comes along with increased confidence on the diagnostic support in the scenario mentioned (Czerwinska *et al.*, 2024).

Awareness and trust are still two separate things, however. Familiarity is what patients feel they know, trust is what patients feel they can rely on the system for. Therefore, the question about their relationship is not a definitional overlap between the two, but is an empirical question. H2 states that there is a positive relationship between artificial intelligence awareness and trust in artificial intelligence assisted medical diagnostic system (Lennartz *et al.*, 2021).

Awareness and Acceptance

Awareness can also be directly correlated with acceptance once usefulness and trust are taken into account. The more familiar a care option is, the more recognisable it can be and easier to think about as part of routine care (Zallipalli *et al.*, 2026). With some understanding of the basic arrangement, patients might be more ready to make a selection regarding it. This direct association is a component of the awareness association, which is not being captured by the two evaluative pathways specified.

The direct awareness relationship is meaningful because willingness can encompass practical understanding and expected benefit and confidence (Osman Ali & Ahmad, 2025). Understanding the terms of the agreement can help to reinforce a concrete commitment to involvement. Thus, the model incorporates awareness as a direct determinant of acceptance and also models the relationships between awareness and acceptance with usefulness and trust. Based on this, H1 is proposed that the artificial intelligence awareness has a positive relationship with patients' views on medical diagnostic systems assisted by artificial intelligence (Sridhar, 2025).

Perceived Usefulness and Acceptance

Perceived usefulness relates to the extent to which AI support could facilitate diagnosis in a meaningful manner for the patient (Uthra Sridhar, 2025). Sociability, contribution to correct identification, contribution to early identification, contribution to decisions and general diagnostic value are all components of the construct. These expectations are related to the reasons for seeking care (Mishra, 2024). They suggest a practical basis for acceptance of a technological contribution in the clinical encounter.

The usefulness relationship proposed touches the idea that the patient is more likely to accept the help of an individual when he or she believes the person is making a contribution toward the care (Correa *et al.*, 2026). This reasoning is consistent with physician oversight as another source of information might be appreciated as an aid to professional judgement. Thus, acceptance may be linked with perceived benefit, even if the patients never interact with the computational system (Hossain *et al.*, 2025). H4 posits that perceived usefulness is positively related to patients' acceptance of artificial intelligence (AI) assisted medical diagnostic system.

Trust and Acceptance

Acceptance means a readiness to allow a system to play an important part in a diagnostic step that has consequences for the individual. Such confidence in that contribution yields a foundation for agreement (Shi *et al.*, 2026). Trust can be particularly germane when patients are unable to assess for themselves the logic of the system or the individual evidence. The decision then involves a judgement about acceptability of reliance on the care arrangement.

Trust and usefulness can coexist and are not interchangeable (Duplaga, 2026). Even a useful option may be refused, if patients do not see it as reliable. A reliable system could be more readily accepted if it is perceived that it is assisting an accountable clinician. The model scrutinises the trust relationship separately and incorporates to it usefulness, awareness and risk, thereby letting the separate association with acceptance be estimated (Chaturvedi, 2025). H5 suggests that there is a positive relationship between trust and patients accepting medical diagnostic systems with the help of artificial intelligence.

Perceived Diagnostic Risk and Acceptance

Perceived diagnostic risk is the fear that help-seeking might lead to a wrong diagnosis or overlooking the fact of an illness. There is also concern about inappropriate subsequent care and adverse consequences for health (Hswen *et al.*, 2024). The construct is related to diagnostic results and not a general discomfort with technology. This specificity renders it applicable to the decision that is posed in the questionnaire and to the practical aspects

that patients might pose in the clinical conversation (Kavitha *et al.*, 2025).

Even when people see a benefit, they may not be willing to do it, due to a risk perception. The importance of consequences remains even if an error is made and you are expecting to benefit (Antes *et al.*, 2021). Similarly, while trust in a support system is not incompatible with all worry about diagnostic uncertainty, neither one is it necessarily the result of the other. Risk coupled with trust makes it possible to model and contrast confidence and concern as separable components of patient appraisal (Oleribe *et al.*, 2025). The H6 suggests that there is a negative relationship between perceived diagnostic risk and patients' acceptance of medical diagnostic systems assisted by AI.

Indirect Relationships Through Usefulness and Trust

There are two parallel tracks in the framework which link awareness and acceptance. On the usefulness pathway, diagnostic expectations were more positively related to familiality, and familiality was more positively related to willingness to receive assistance. In the trust pathway, 'awareness' is linked to 'confidence in diagnostic support', and 'confidence in diagnostic support' is linked to 'willingness'. These pathways offer a coherent account of the potential statistical relationship between knowledge and evaluation and acceptance (Seitenov *et al.*, 2026).

The simultaneous direct awareness path makes it possible to determine if these indirect relationships occur in conjunction with another awareness association through the analysis. If a positive direct and indirect estimate exist, it would suggest that there is a complementary pattern within the model given (Augustine *et al.*, 2024). The pathways are evaluated as statistical linkages between the cross-sectional constructions. There is a positive indirect relationship between awareness and acceptance based on perceived usefulness, as suggested by H7. H8 suggests that there is a positive indirect link between awareness and acceptance as mediated by trust (Zhu *et al.*, 2026). The conceptual framework of the eight hypotheses is also shown in Figure 1.

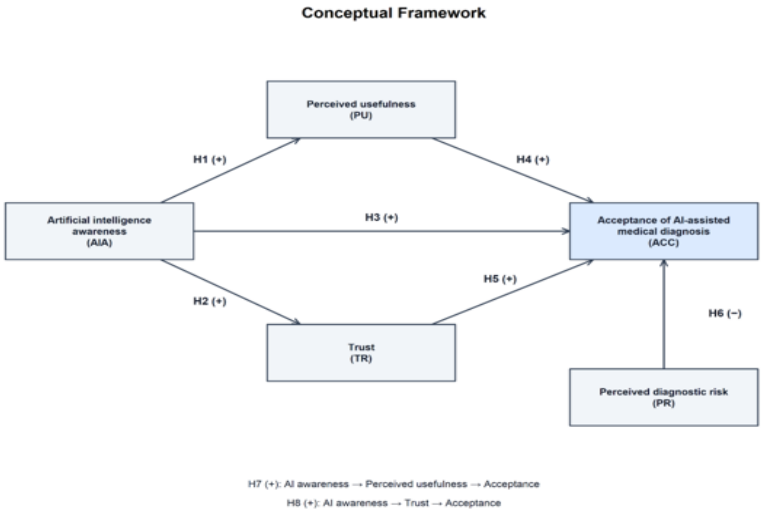


Figure 1: Conceptual framework and hypothesised relationships

MATERIALS AND METHODS

Research Design and Analytical Sample

The study used quantitative cross-sectional design which focused on the relationships between patients' awareness and patients' opinions of AI assisted diagnosis. For the analytical material, 390 questionnaire records were used, including patient background and 20 measurement indicators (Schaffernak *et al.*, 2026). The unit of analysis used is the individual respondent. A diagnostic scenario was used in the investigation of the acceptance, and the model consisted of five constructs, six direct relationships and two specific indirect relationships.

For the questionnaires, eligibility criteria were defined as age 18+, attending a facility for their own healthcare, comfort and ability to fill out a short survey. Having previously experience with artificial intelligence (AI) assistants was not a requirement for eligibility. Thus, the same diagnostic scenario was used to assess assistance to respondents, even when they did not report use of AI in their personal diagnosis.

The content of the participant information included a statement of voluntary participation, the ability to skip questions or to stop before submitting and no consequences for medical care. It asked the respondents to refrain from providing names, telephone numbers, hospital identification numbers, or diagnoses (Foresman *et al.*, 2024). The protocol included the process for seeking consent prior to being screened for eligibility, as well as for summarizing confidential responses. These are provisions that outline the participant information and consent procedure included in the study instrument.

Questionnaire Structure and Construct Measurement

Five multi-item measurement sections, eight background questions, and screening questions were part of the instrument. Background characteristics included age,

gender, education, residential setting, care setting, facility type, internet use and prior knowledge of the use of artificial intelligence in diagnosis. These variables were used to describe the analytical sample. They were not included as auxiliary pathways in the structural model.

The measurement items employed a five-point agreement scale (from strongly disagree to strongly agree). The additional UNABLE TO JUDGE category was separated from the NEUTRAL category. The artificial intelligence awareness was placed in front of the explanatory scenario and the respondents were asked to think about their current state of knowledge prior to the survey. The remaining pieces mentioned a standard AI definition: Software used to interpret medical data and recommend results for a doctor to help them determine a health issue (Phelps *et al.*, 2026).

The scenario included a doctor checking the results with other medical information and making the final diagnosis. It also stated that systems are capable of making the mistake and the benefits and risks will differ. Respondents were instructed to think about this hypothetical situation even if they had not been given assisted care. This common reference helped tie the usefulness, trust, risk, and acceptance items to the same clinical arrangement and thus helped ensure consistency in the meaning of the measured constructs.

Four reflective indicators were used for each construct. Awareness included what participants have learned and what they know. Usefulness included accuracy, earlier identification, diagnostic decisions and overall value. Trust was defined as confidence, dependability, reliability and reliance on support. Diagnostic risk included incorrect diagnosis, missed signs of illness, inappropriate follow up and health risk (Osnat, 2025). Acceptance incorporated willingness, choice, agreement and intention to do in the future. Higher scores indicated increased amounts of the identified construct, including higher concern with the diagnostic risk items.

Data Screening and Descriptive Analysis

For the 390 measurement cells supplied, there were no invalid measurement values and no missing measurement cells were identified during the screening. Because within this sample, no records were excluded due to either the lack of measurement responses or invalid responses, the final sample size for analysis was 390. There was also no matching complete 20 item profiles identified via screening. For all measurement analyses reported, the complete analytical sample (no cuts) was used, with no imputations for missing measurement cells made.

Respondent's background characteristics were summarised by frequencies and percentages. Descriptive data and statistics were presented in mean, standard deviation, minimum and maximum.

Measurement and Structural Model Assessment

Standard partial least squares structural equation modelling with Mode A weights was used for the reflective measurement blocks. The analytical output revealed: version of R: 4.6.1; version of seminr: 2.6.0. Outer loadings, indicator reliability, Cronbach's alpha, rho A, composite reliability and average variance extracted were examined in the measurement assessment (Baghdadi *et al.*, 2024). The loadingings were evaluated against the reported reference of 0.708 and an average variance extracted of more than 0.50 meant that more than half the variance of the indicators of a construct, on average, was captured in the construct.

Heterotrait monotrait ratio (absolute correlations) was computed to check for the discriminant validity. The threshold value of 0.85 was used. Two-sided percentile 95% confidence intervals for each ratio were obtained from the raw data row bootstrapping of 10,000 resampled replicates. Inner variance inflation factors were used to check structural collinearity. The results of this sequence confirmed the sufficiency of the measurement differences prior to their interpretation of the coefficients associated with the relationship between constructs.

They developed a structural model, with levels of awareness predicting usefulness, trust, and acceptance, and usefulness and trust, in addition to diagnostic risk, predicting acceptance. For statistical inference 10,000 retained bootstrap draws were used. Standard errors, t statistics, two-sided p values, based on a normal approximation using bootstrap standard errors, were reported and percentiles of 95% confidence intervals. Both of the indirect relationships were tested via their bootstrapped estimates and confidence intervals. Relationships were accepted as statistically supported, where the directionality of the relationships was as hypothesized, and the inferential results were significant.

R squared and the adjusted R squared were used in examining explanatory performance in case of endogenous constructs. Effect sizes were determined by performing omitted path PLS re estimation based on small, medium, and large values of 0.02, 0.15, and 0.35 respectively. Predictive assessment was performed using direct antecedent indicator, and the 10-fold cross validation was repeated 10 times, with the same folds used for the PLS and linear benchmarks. Pooling of held out errors was done across repetitions (Karger, 2026). Meanwhile, squared error obtained from Q squared predict was compared to the training mean benchmark, and root mean squared error and mean absolute error was used to compare with the linear benchmark.

RESULTS AND DISCUSSION

Analytical Sample and Respondent Characteristics

A total of 390 records were kept for analysis purposes. There were no invalid or missing measurement values, enabling consistency across the five constructs and all structural relationships. The sample profile is summarised in table 1. There was a response from all five age bands, the largest being from the age band 18-29 and 30-39. These groups represented a total of 52.3% of respondents (n = 204). To represent older and younger adult patients,

10.8% of the sample were 60 years of age or older.

Of those who were asked, males accounted for 53.6% and females 43.6%, and others or 'not stated' 3.2%. Education levels varied from none to bachelor's or higher. The largest share of this population held secondary education (27.4 %), followed by bachelor's-level or higher education (25.1 %) and higher secondary education (23.8 %). The distribution indicates that those who responded to the diagnostic scenario had a diverse formal educational background.

Of the total sample 53.3%, 36.4% and 10.3% were urban, rural and peri urban residents respectively. The majority of respondents were from outpatient care (64.1%), diagnostic centres (22.1%) and inpatient care (13.8%). Private facilities accounted for 50.5% and the public facilities 44.4%. These figures convey information to help interpret the patient evaluations, but not that the structural relationships between the categories of facilities and residence differed; comparisons among the structural relationships of categories are not presented in the model.

57.4% said they used internet daily while 14.4% said that they never used it. 15.4% had been previously informed that they had received a diagnosis that involved the use of artificial intelligence. 39.2% responded with no and 45.4% with don't know. It is understandable that the context of the well-defined scenario is particularly important in interpretation because of the overlap of substantial uncertainty regarding prior use. Responses include reception of the described assistance, and should not be confused with independently verified exposure to AI.

Table 1: Respondent characteristics

Characteristic	**Category**	**n**	**%**
Age	18–29	105	26.9
	30–39	99	25.4
	40–49	81	20.8
	50–59	63	16.2
	60 or above	42	10.8
Gender	Woman	170	43.6
	Man	209	53.6
	Another identity	5	1.3
	Prefer not to answer	6	1.5
Education	No formal schooling	31	7.9
	Primary	61	15.6
	Secondary	107	27.4
	Higher secondary	93	23.8
	Bachelor's degree or above	98	25.1
Residence	Rural	142	36.4
	Urban	208	53.3
	Peri-urban	40	10.3
Care setting	Outpatient	250	64.1
	Inpatient	54	13.8
	Diagnostic centre	86	22.1
Facility type	Public	173	44.4
	Private	197	50.5
	Other	13	3.3
	Not sure	7	1.8
Internet use	Never	56	14.4
	Less than weekly	36	9.2
	Weekly	74	19.0
	Daily	224	57.4
Prior AI use notification	Yes	60	15.4
	No	153	39.2
	Not sure	177	45.4

Construct Descriptives

All five-construct means are fairly concentrated at the middle point of the agreement scale. The mean value for each of the five factors—awareness, perceived usefulness, trust, perceived diagnostic risk, and acceptance—was, respectively, 3.046, 3.039, 3.078, 3.051 and 3.036. The standard deviations for all of the constructs ranged from .997 to .1015 and the range of observed scores was 1 to 5 for each of the constructs. These descriptive findings, along with principal reliability and validity statistics are presented in Table 2.

The average responses do not show consistent high levels of acceptance or rejection of the diagnostic organisation. While the numerical differences between constructs were small, the highest mean was attained by trust and no comparative significance tests were performed (Jeyakumar *et al.*, 2022). The standard deviations around each mean are pertinent in a structural model because they consider if individuals whose mean score is higher on one construct tend to be different on another. A midpoint average can thus exist alongside very strong and statistically valid links between individual ratings.

Table 2: Construct descriptives and measurement quality

Construct	Mean	SD	Alpha	rho A	CR	AVE
AIA	3.046	1.013	0.870	0.873	0.911	0.719
PU	3.039	1.007	0.859	0.862	0.904	0.702
TR	3.078	0.997	0.852	0.852	0.900	0.692
PR	3.051	1.015	0.861	0.874	0.905	0.705
ACC	3.036	1.010	0.856	0.858	0.903	0.699

AIA = artificial intelligence awareness; PU = perceived usefulness; TR = trust; PR = perceived diagnostic risk; ACC = acceptance; SD = standard deviation; CR = composite reliability; AVE = average variance extracted. N = 390 for each construct.

Indicator Reliability and Internal Consistency

The loading reference reported was 0.708 and all of the 20 indicators were above this. Awareness loadings ranged from 0.833 to 0.865, usefulness from 0.822 to 0.854, trust from 0.824 to 0.846, risk from 0.822 to 0.861, and acceptance from 0.811 to 0.857. Reliability indicators of the corresponding indicators were between 0.658 and 0.748. The results of these tests suggested that the indicators of the fitted measurement model were consistent with the intended constructs.

Cronbach's alpha ranged from 0.852 to 0.870, rho A from 0.852 to 0.874, and composite reliability from 0.900 to 0.911. This pattern was repeated in all five of the measurement blocks. The awareness construct had the highest composite reliability (0.911), the others were very close to 0.90. The results support the use of the four indicators within each block as related expressions of the corresponding underlying patient evaluation.

Average variance extracted was between 0.692 and 0.719 with the lowest being trust and the highest being awareness. Convergent validity was supported by all values that were greater than 0.50. This contributes to the loading and internal consistency results: there was some overlapping among the indicators for their constructs, but some coherence in responses within a given block. The evidence of measurement indicated that all five constructs should be retained in order to be structurally interpreted.

Discriminant Validity and Structural Collinearity

The heterotrait monotrait ratios varied from 0.049 to 0.544, all of which were less than 0.85. Trust/Acceptance had the highest ratio, followed by Awareness/Acceptance. Each upper bound of the bootstrapped 95% intervals was less than 0.85, with the highest upper bound being 0.626. The evidence thus confirmed that there was discrimination between the constructs, namely between usefulness, trust and acceptance, which are conceptually related.

The difference is significant in practice (Baikadolla, 2025). The positive relationship between the two dispositional factors, namely trust and acceptance, can be attributed to the fact that the two factors were not treated as measured as the same. Similarly, there was found to be a separation of awareness and usefulness/trust. The low ratios related to risk also suggested that diagnostic concern was a distinct aspect of evaluation. Inner variance inflation factors were between 1.000 and 1.407. These values suggested that there were no material collinearity problems when estimating the structural relationships specified.

Direct Relationships and Hypothesis Testing

Each of the six direct hypotheses was confirmed and each relationship was significant at the $p<0.001$ level. The coefficients, bootstrap statistics, confidence intervals, and effect sizes are shown in table 3. After the inclusion of the two evaluative constructs, there was positive association between awareness and usefulness, as well as between awareness and trust, and the association between awareness and acceptance remained positive (Westerbeek *et al.*, 2026). There were positive relationships between usefulness and trust and acceptance; and the expected negative relationship between perceived diagnostic risk and acceptance.

Awareness had a beta of $\beta = 0.410$ with a 95% confidence interval ranging from 0.328 to 0.492. The effect size

Table 3: Direct relationships and hypothesis tests

Hypothesis	Path	β	t	95% CI	f^2
H1	AIA → PU	0.410	9.779	0.328 to 0.492	0.203
H2	AIA → TR	0.424	10.288	0.343 to 0.504	0.219
H3	AIA → ACC	0.190	4.157	0.102 to 0.279	0.044
H4	PU → ACC	0.261	6.120	0.177 to 0.344	0.094
H5	TR → ACC	0.347	8.424	0.267 to 0.428	0.167
H6	PR → ACC	-0.256	6.854	-0.331 to -0.185	0.110

All six hypotheses were supported; all $p < 0.001$. CI = percentile bootstrap confidence interval based on 10,000 retained draws. The t statistics are absolute values.

was 0.203 which is in the medium reference category. This finding aligned with H1, with participants with higher self-reported prior knowledge showing a higher expectation of the potential for artificial intelligence support in effective diagnosis. The association is in line with the conceptual role of awareness, which is to make the purpose of the support comprehensible and relate it in a personally relevant manner to diagnostic benefits.

The awareness and trust relationship was found to be β= 0.424, the 95% confidence interval was 0.343 to 0.504 and the effect size was 0.219. Hence, H2 was endorsed. This finding indicates that awareness was associated with perceived utility, as well as with trust in the diagnostic aids. The relative similarity of the magnitude of the awareness coefficients indicates that knowledge and familiarity were pertinent to both evaluative dimensions and there is no formal assessment of whether the two coefficients differ. Awareness remained directly associated with acceptance (β = 0.190, 95% CI: 0.102–0.279). The effect size corresponding to this was 0.044. The usefulness and trust did not fully support the awareness association in the defined model, as evidenced by the support of H3. It was found that the direct coefficient was smaller than the coefficients connecting awareness to its two evaluative results, indicating that both direct and indirect statistical relationships of familiarity to acceptance were involved.

The 95% confidence interval for the regression coefficient of perceived usefulness was (0.177, 0.344), which was positively significant for acceptance with a regression coefficient β = 0.261. It was found that its effect size was 0.094 to support H4. Deliberate desire to help make accurate, timely and improved diagnostic decisions was expressed by patients who had expressed an expectation that a contribution would be made. The outcome is that acceptance is tied to anticipated value in the clinical task, and communicating to the patient tied to their care, is supported.

Among the predictors of acceptance, the one that had the highest positive direct coefficient was trust with β = 0.347. The 95% confidence interval for it was 0.267 to 0.428, and the effect size was 0.167 which was in the medium reference category. H5 was supported. Numerical Ranking is a relative ranking with respect to the other variables, indicating that the confidence in diagnostic support is a key element of the fitted acceptance model. It does not necessarily mean that the trust coefficient was statistically larger than each of the other coefficients does, however, give a descriptive priority for interpreting the observed pattern.

The relationship of perceived diagnostic risk was β = −0.256, with a confidence interval ranging from −0.331 to −0.185. The effect size was 0.110 which is supporting H6. Participants who felt more concerned about having a wrong diagnosis, having their illness not diagnosed, and the lack of followup were less willing to receive help. This relationship co-existed with the feeling of being aware, useful and trusted. Patients' concerns about the meaning of the diagnosis thus added to their actual contribution more than their expectation of benefits and trust in system reliability.

Indirect Relationships and Complementary Mediation

Specific indirect hypotheses were confirmed (with p value < 0.001). There was an indirect AA through usefulness of 0.107 with 95% of the interval: 0.069 to 0.151. The indirect association by trust was 0.147 (0.106 - 0.195). Zero was not in either of the intervals. The results for mediation are reported in Table 4, which satisfy H7 and H8 respectively.

Table 4: Specific indirect relationships

Hypothesis	Path	Estimate	t	95% CI
H7	AIA → PU → ACC	0.107	5.148	0.069 to 0.151
H8	AIA → TR → ACC	0.147	6.471	0.106 to 0.195

Both hypotheses were supported; both $p < 0.001$. Positive indirect and direct awareness relationships indicate a complementary pattern within the specified model.

The positive indirect estimates were accompanied by a positive direct awareness coefficient. This trend fits with the concept of complementary partial mediation in the model. The Awareness was linked to acceptance via expected usefulness and confidence, and another direct link remained between Awareness. N = 120K: The indirect effect of the trust pathway was numerically larger than the indirect effect of the usefulness pathway. The results presented for the two pathways are in favor of each pathway alone, but a separate test of difference was not rendered.

The sum of the two specific indirect estimates reported is about 0.255, which is a combined indirect point estimate. The direct coefficient adds to this value, yielding an estimated total awareness point of ~0.445. These are simple arithmetic summaries that tell about the fitted pathway structure and do not include a separate bootstrap test of the combined or total estimate. The pattern is substantively one which suggests that awareness may be most informative when it is viewed in conjunction with the evaluative judgements issued with it; it is not simply indicative of familiarity, but of familiarity plus evaluation.

Explanatory Power and Predictive Assessment

The awareness model accounted for 16.8% of variance in perceived usefulness and 18.0% of the variance in trust. Both adjusted R squared values were equal to 0.166 and 0.177 respectively. The four predictors accounted

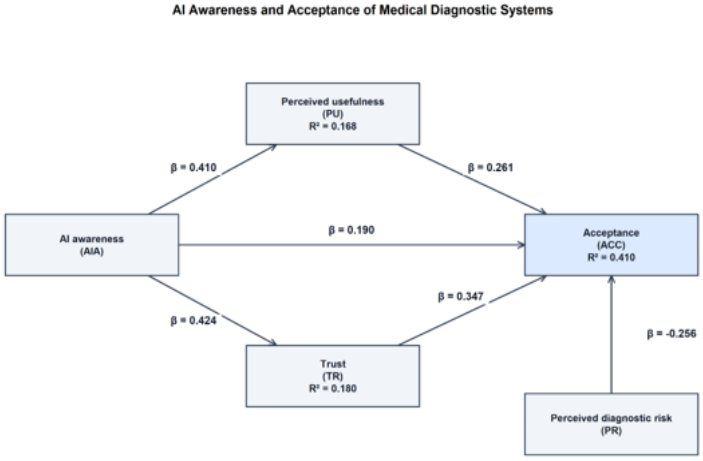


Figure 2: Estimated structural model with standardised coefficients and explained variance

for 41.0% of the variance and an adjusted R squared of 0.404 for acceptance. The result of the estimated structural model is presented in figure 2. The acceptance result is evidence of the explanatory relevance of the four factors of familiarity, anticipated benefit, confidence and diagnostic concern collectively in the given patient scenario.

Table 5: Predictive assessment of acceptance indicators

Indicator	Q^2 predict	PLS RMSE	LM RMSE	PLS MAE	LM MAE
ACC1	0.233	1.077	1.097	0.889	0.901
ACC2	0.299	1.040	1.055	0.853	0.852
ACC3	0.281	0.973	0.993	0.802	0.827
ACC4	0.287	1.030	1.032	0.845	0.843

RMSE = root mean squared error; MAE = mean absolute error; LM = linear benchmark. Results pool held out errors from 10 fold cross validation repeated 10 times, with identical folds for both models.

Positive predictability (Q squared) was obtained in the predictive assessment for all four indicators of acceptance (Q squared ranged between 0.233 and 0.299). There were 3,900 predictions held out for each indicator from the 10 cross validation repetitions. A repeated prediction is one prediction for the same sample that was re-partitioned and not an additional independent respondent. Table 5 revealed that all four PLS root mean squared errors were less than the linear benchmark errors. The root mean squared errors of the PLS were between 0.973 to 1.077 and the linear benchmark values were between 0.993 and 1.097. The differences were in favour of PLS on all indicators, though the size of the differences varied. There were mixed results when comparing the mean absolute errors, with PLS being lower for ACC1 and ACC3, and the linear benchmark being slightly lower for ACC2 and ACC4. Comparisons of the root mean squared errors and positive Q squared predict provide the best support for the predictive conclusion, therefore. It is about prediction of responses to acceptance, where indicators of the direct antecedents are available.

Integrated Interpretation and Practical Implications

The results indicate that acceptance is not a unipolar assessment, but rather a more holistic assessment of the attitude towards technology. Awareness was linked to both perceived usefulness and trust to use, which in turn was linked to acceptance, and risk was a separate negative factor (Hemphill *et al.*, 2023). This combination often accounts for the fact that although a patient may see the potential value in a diagnosis, he/she may still have some doubts about participation. The model is able to accommodate these concurrent judgements, and offers a structured account of how they come into relation with willingness within supervised care.

The focus of the trust result is how reliable patients consider the support arrangement to be. An explanation simply stating that a system is artificial intelligence can often leave it unclear to others why they should trust this system. Communication might instead explain what information the system is looking at, how the physician uses the information and who is still responsible for interpreting the information obtained by the system. It is important to note that it is not an analysis of the effect of a specific communication intervention—these are practical implications from the constructs.

The usefulness relationship helps with explanations related to the diagnostic task. Patients can be told about the proposed role of the assistance in conveying the information and helping the medical decision-making process. These explanations should not imply that the findings of the acceptance of the study are proof that a specific system enhances accuracy or clinical results. The dependent variable examined was the perceived usefulness, which is related to the willingness that the patient has in the described scenario (Wewetzer *et al.*, 2026).

The negative risk association encourages open dialogue regarding errors and the clinical action for unclear/cross contradictory findings. Risk was separated from trust and reassurance that was solely dependent on reliability might not address consequential concerns (Czerwinska *et al.*, 2024). Patients might want to know how a finding is verified, how additional testing is done and how to ask questions during treatment. Understanding and resolving these issues can help to clarify the choice and maintain patient autonomy in choosing to accept or reject assistance.

Sample profile also helps in communication. There has been an evaluation of a scenario from various backgrounds as evidenced by varied education levels and Internet use. Patient information may thus be delivered using simple language and can be made clear without requiring background technical knowledge. The lack of certainty on the part of many respondents concerning the use of artificial intelligence in the past also justifies a clear distinction of when one is talking about the use of AI in diagnosis. These are recommendations made based on the overall profile and framework and not based on assigning demographic groups to different acceptance pathways.

The combination of both results, explanatory and predictive, increases the relevance of the integrated model for the understanding of patient intentions (Lennartz *et al.*, 2021). The measurement evidence defines the constructs, the structural estimates define the association between the constructs, and the cross validation verify the prediction beyond the set of observations in each training fold. All these elements facilitate a coherent interpretation focused on informed understanding, perceived clinical significance, secure assistance, and an explicit focus on diagnostic concern.

CONCLUSION

This study focused on the perceived usefulness, trust, and perceived diagnostic risk; AI awareness and acceptance for medical diagnostic systems. All the six direct hypotheses and the two indirect ones were supported by analysis of 390 complete questionnaire records. Awareness positively correlated with usefulness, trust, and acceptance. Acceptance was positively related to usefulness and trust, negatively related to perceived diagnostic risk. The model accounted for 41.0% of the variance in acceptance and had positive predictive relevance in all 4 acceptance indicators.

The most salient direct positive predictor numerically and with a medium effect size was trust. Awareness exhibited medium effect sizes in relation to usefulness and trust as well. The notable indirect routes point to expected diagnostic benefit and support confidence as one way in which the awareness association was expressed. Their co-occurrence with a positive direct path is an integrated account of acceptance which acknowledges the familiarity and the evaluations that go along with it.

When creating a patient facing artificial intelligence (AI) assisted diagnosis, healthcare organisations should look at providing clear explanations of the clinical arrangement. Information should include the name of the support function, how the information is used in the diagnostic process and where the doctor fits into that process as far as the final judgment is concerned. Communication should relate what is being offered to its intended diagnostic use and give patients a chance to ask questions.

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