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Innovations In Non-Invasive Liver Disease Diagnostics (E.G., Fatty Liver, Cirrhosis)

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ABSTRACT

Background: Fatty liver disease (FLD) and cirrhosis are some of the major diseases of the liver and a major cause of morbidity. Liver biopsy, despite being a useful method of diagnosing the disease, is an invasive technique, expensive, and accompanied by risk and pain. Non-invasive diagnostic methods that are under development today, like FibroScan, Shear Wave Elastography (SWE), Magnetic Resonance Elastography (MRE), and diagnostics with the use of biomarkers, are good options. Nonetheless, they are not evenly adopted among different stakeholders and are assumed to be successful.

Objective: Due to this purpose, this research study will determine the level of awareness, images, and usage of non-invasive technologies for liver disease diagnosis among medical workers, investigators, and patients. It also explores the correlation between the major determinant measures, which include trust in technology, perceived effectiveness, cost concern, and availability.

Methods: A Quantitative cross-sectional survey consisting of 250 respondents spread across five provinces of Pakistan was used. Data on demographic factors, awareness, perceived effectiveness, practicing behaviour, and factors were obtained with the help of a structured questionnaire. Some of the statistical analyses used included normality testing, reliability testing (Cronbach's Alpha), construct validity through Principal component analysis (PCA), Pearson correlation, and multiple linear regression.

Results: The findings according to the data indicated non-normality in the data of age and normality in the data of years of experience. The internal consistency was good, and Cronbach's Alpha was 0.871, which demonstrated good reliability of the survey instrument. PCA advocated construct validity, which had a cumulative variance above 70 percent. Pearson's correlation revealed a positive correlation among all the important variables. The predictors of adoption of diagnostic tools were found to be cost concern, trust in technology, and awareness by multiple regression analysis. The positive relationship.

between R and adopting behaviour was 61.4 percent (R 2 = 0.614).

Conclusion: Liver diseases are being tested in terms of non-invasive diagnoses and have begun to achieve popularity. The widespread spread of innovations is highly dependent on aspects that include cost, accessibility, trust in the technology, and awareness. They can be largely improved by offering better training, reducing the cost of implementation, and exposure to technology. The paper presents utilitarian knowledge in healthcare policy formulation, clinical decision making, and diagnostic innovation research..

Keywords: Non-invasive diagnostics, liver disease, fatty liver, cirrhosis, Fibro Scan, usage of technology, Cronbach, Alpha, correlation Pearson, regression analysis

1. INTRODUCTION

Fatty liver disease (FLD) and cirrhosis are the most widespread causes of morbidity and mortality of liver diseases in the world. The liver is the most influential organ in the metabolism process, detoxification, and nutrient reserve; thus, liver health is important to general well-being. When such diseases advance, they may also result in severe complications in terms of liver failure, liver cancer, among others, and even death. Conventionally, invasive procedures such as liver biopsy have been used to diagnose and monitor liver diseases, and though they are effective, they pose dangers of bleeding, infection, and pain to the patient. This has necessitated the coming up with non-invasive modes of diagnosis since it is safer and friendlier to patients. The new methods of diagnosis, the use of non-invasive diagnostic methods, ease the situation and reduce the risks of a liver disease diagnosis (Franczak et al., 2025).

Use of sophisticated technologies, including imaging methods, biomarkers, as well as artificially intelligent tools, is used in the diagnosis and severity of liver diseases without having to take a physical sample of the tissue. As an example, check the Fibro Scan, an ultrasound version of transient elastography that is used to quantify liver stiffness, which in turn is related to liver fibrosis and cirrhosis. There is also the use of Shear Wave Elastography (SWE) and Magnetic Resonance Elastography (MRE) to measure the stiffness of the liver as well as the MRI Fat Fraction (PDFF) which measures the content of fat liver which is useful in the diagnosis of non-alcoholic fatty liver disease (NAFLD) and non-alcoholic steatohepatitis (NASH). Also, there are now biomarkers that are used to determine the extent of liver fibrosis (like the ELF test or Enhanced Liver Fibrosis test), which one can assess without invasive activities like a liver biopsy (Hernandez et al., 2025).

Nevertheless, even though the clinical utility of these non-invasive methods has already been confirmed, they are not yet standardized across clinical practice, and awareness, acceptance, and application outcomes in various medical facilities and organizations are varied. The main issue that arises is the comprehension of the efficacy, the obstacles to practices, and the aspects of utilization of these non-invasive diagnostic methods. Past research has revealed that these technologies have been highly acclaimed in terms of their capacity to determine the stage of liver disease development and deliver proper results at the same time; however, wide application of the same has not been consistent. Other factors, which are the cost, availability of equipment, patient comfort, and clinical guidelines, are exerting a significant influence on whether these diagnostic methods will be incorporated into clinical practice or not (Righetti et al., 2025).

Also, although these methods have a non-invasive character, an uncertainty regarding the validity of these methods, especially at the initial stages of the liver disease process, is a very crucial factor. This research will set out to examine the adoption, the pattern of usage, the effectiveness, and the perceived obstacles of non-invasive means of liver disease diagnosis. Using a survey among healthcare professionals, researchers, and patients, this paper will assess the level of familiarity these stakeholders have with such diagnostic techniques and determine some factors that guide their adoption. It will also evaluate associated perceived advantages and difficulties of the technologies with regard to their proposed replacement of the traditional invasive actions, such as liver biopsies. Collecting information using a wide scope sample will help to have a complete picture of the present situation with non-invasive liver disease diagnostics (Garg et al., 2025).

Besides, the research aims at determining the reliability of questionnaires, which will be utilized to assess the perceptions of these diagnostic techniques. It plays a critical role because how efficient these tools become not only depends on their technological aspects, but also on their ability to be incorporated in clinical practice as well as their acceptance in the medical community. The results of this study will be used in future studies on how better diagnostic methods can be identified and how these methods will be embraced in the clinical world to lead to improved outcomes for patients in managing liver diseases. However, the prospect of non-invasive liver disease diagnostics is fine, and some challenges prevent its further implementation. An example of such adversities is the high cost of specialized diagnostic tools, which may become too burdensome to healthcare institutions, and especially those that are low-resourced (Popowski et al., 2025).

Moreover, these diagnostic technologies are frequently restricted to special centres, and patients in rural or underserved places are not able to obtain such technologies. In a few instances where they are available, healthcare providers might not be willing to employ the methods because they either lack the training or experience with the methods, and therefore, it might

be a stopper on their implementation as well. Furthermore, the precision of some non-invasive approaches is a matter of continued investigation. Although the vast majority of technologies, such as Fibro Scan and those functioning based on MRI, are rather trustworthy, they still raise issues concerning their efficiency in forecasting the early manifestations of liver disease or having other related conditions, which may contribute to the disorders taking place with the performance of results (Wu et al., 2025).

Therefore, although such innovations come with a high level of benefits, the continuous attempts to enhance accessibility, affordability, and the accuracy of the diagnostics are essential in separate full-scale usage. This paper attempts to shed light on these issues through a sample survey among professionals in the healthcare sector, researchers, and patients, and to provide some practical suggestions to address these obstacles. By gaining a better idea of the perceptions and ways of using non-invasive diagnostic methods, through a more comprehensive psychological outlook, the study aims to help in perfecting these technologies and making them more reachable, precise, and incorporated into regular clinical life (Chauhan et al., 2025).

Literature Review

Diseases of the liver, such as fatty liver disease (FLD) and cirrhosis, are developing major health problems all over the world because of the high numbers of people affected, and the serious conditions that may arise, including failure of the liver and liver cancer. Liver, due to its importance in balancing different metabolic processes, is very significant in enhancing body health. In the past, liver biopsy to aid in the diagnosis of liver diseases was an invasive procedure and is still used today, although it poses risks, like bleeding, infection, and discomfort to the patient. These dangers, together with the desire to have methods that are less invasive, cost-effective, and friendly to their patients, have led to the innovation of non-invasive diagnostic technologies. The different innovations in non-invasive liver disease diagnostics are explored in this literature review by discussing the development of non-invasive techniques, their advantages, and disadvantages, and how these methods would be adopted in clinical practice (Armanda, 2025).

Non-Invasive Diagnostic Techniques of Liver Diseases

In the recent twenty years, some non-invasive methods have been introduced that benefit of being safe and effective methods of diagnosing fatty liver disease, cirrhosis, and liver fibrosis through liver biopsy. Such approaches are mostly aimed at determining liver stiffness, fat, and the biomarker that can be used to understand liver condition without taking a sample. Transient elastography (Fibro Scan) is one of the most used non-invasive tools. Fibro Scan with shear wave-based liver stiffness measurements has been demonstrated to correlate strongly with liver fibrosis and cirrhosis. Its use is effective in the diagnosis of significant fibrosis and cirrhosis among chronic liver disease patients, and non-alcoholic fatty liver disease (NAFLD) and hepatitis C (Jin et al., 2025).

Fibro Scan has been confirmed to be repeatable and has several pros, including the fact that it is fast, pain-free, and less expensive than liver biopsy. Shear Wave Elastography (SWE) would also be another non-invasive diagnostic tool that is based on similar principles to Fibro Scan but involves the use of ultrasound waves to measure liver stiffness. Of special advantage is the fact that SWE is suitable for point-of-care testing and therefore more accessible to outpatients. Recent research has demonstrated that SWE is accurate in predicting liver fibrosis and cirrhosis in patients with chronic liver diseases, including hepatitis B and fatty liver. Nevertheless, other factors like obesity, liver congestion, among other factors, may affect the accuracy of SWE, hence, compromising its ability to determine the level of liver stiffness (Nikou et al., 2025).

These drawbacks raise the problem of continued research in the future in order to enhance the accuracy of the technique in other categories of patients. Besides elastography-based modalities, there is another newer non-invasive technique, namely magnetic resonance elastography (MRE), that is used to determine the liver stiffness. MRE has the benefit of arranging high-resolution maps of liver stiffness with MRI, and it is shown to be more effective than other methods of elastography due to higher accuracy and tissue identification. MRE can be used with obese or ascitic patients, particularly those who may not be adequately diagnosed using other non-invasive procedures. The use of MRE is, however, limited to academic and specialized clinical settings due to its high cost and unavailability of the product. Nonetheless, MRE is very useful in the detection of liver fibrosis and cirrhosis among various chronic liver diseases, e.g., non-alcoholic fatty liver disease (NAFLD) and alcoholic liver disease (Villanueva Raisman et al., 2025).

In addition to imaging-based approaches, biomarker-based assessment of liver diseases has been developed in plenty of ways. Blood-based Fibro Test that is based on the combination of multiple biomarkers (with the association of hyaluronic acid and apolipoprotein A1) offers a non-invasive measurement of liver fibrosis. There are several studies to support the Fibro Test as a valid method of assessing liver fibrosis and biopsy as an alternative, both in clinical practice and the studies. The other common biomarker-based test is the Enhanced Liver Fibrosis (ELF) test, which combines multiple biomarkers to determine the level of liver fibrosis, e.g., tissue inhibitor of metalloproteins (TIMP1) and hyaluronic acid. The ELF test has been useful in the diagnosis of liver fibrosis in individuals with chronic induced diseases of the liver, particularly hepatitis C, with good correlation between liver biopsy and the test (Wen et al., 2025).

Artificial intelligence (AI) in liver disease diagnosis is an emerging interest that continues to grow. Non-invasive diagnostic techniques are receiving AI algorithms in order to improve their level of accuracy and efficiency. As an example, ultrasound

elastography in combination with AI tools is used to enhance the perception of liver stiffness and fibrosis. Machine learning technologies have been engineered to operate on large masses of data collected using imaging methods such as MRI and CT imaging, which assist clinicians in identifying early signals of liver conditions that may not be seen with the human eye. The diagnostic value of AI-based tools can transform the diagnosis of liver diseases, reducing the time it takes to detect diseases, having customized treatment strategies, and finally, changing patient outcomes. The use of AI in clinical practice, however, presents a challenge because the training of the algorithms requires large and heterogeneous data, and the regulatory process of approving medical devices (Zhang et al., 2025).

Benefits and Limitations of Non-Invasive Diagnostic Methods

The merits of a non-invasive diagnostic procedure are many. Among the most important advantages, it can be pointed out that these methods provide an alternative, less painful, and safer than liver biopsy. To patients, this implies that they do not have to incur the risk of complications and pain of invasive therapies. Further, non-invasive practitioners are usually more economical, especially in low-income countries, where the financial burden of performing a biopsy and hospitalization may prove to be overwhelming. Non-invasive procedures, such as fibro scan and SWE, are also quicker, can be done on an outpatient basis, and, thus, lessen the load on healthcare systems, streamlining the number of patients (Wang et al., 2025).

Nevertheless, the non-invasive types do not have some limitations. Although they are very beneficial in terms of patient comfort/convenience, their accuracy may be affected by a number of aspects, including obesity, ascites, and steatosis. As an example, although the efficiency of Fibro Scan is very high in detecting the presence of advanced fibrosis, it substantially decreases when there is a great degree of liver steatosis or among obese patients. Likewise, the SWE method may present lower sensitivity when there is fatty liver, thereby making it difficult to diagnose NAFLD. The cost of certain forms of non-invasive techniques is another issue, especially those that are MRI-based, as they are still beyond the means of many healthcare institutions, as the techniques are slightly expensive and can be impractical (Lazaros et al., 2025).

Research Methodology

In this study, a quantitative research design will be applied to observe the current developments in innovative non-invasive methods of diagnosing liver diseases, and in particular, the topic of fatty liver and cirrhosis. The main idea is to evaluate awareness, effectiveness, and the level of adoption of those diagnostic novelties among healthcare providers and patients in Pakistan. The method used to collect data was a cross-sectional survey, since it was necessary to extract information at a particular time and cover a variety of participants who could be gastroenterologists, radiologists, hepatologists, general practitioners, and diagnosed patients (Heyens et al., 2021).

Population and sample

The research sample will be within the healthcare professional and patient population within the five largest provinces of Pakistan, including Punjab, Sindh, Khyber Pakhtunkhwa, Baluchistan, and Gilgit-Baltistan. The purposive sampling technique was used to guarantee that only the persons with related experience or diagnosis were taken into the sample. One hundred and fifty respondents were surveyed, which included 75 medical specialists and 75 interviewed patients who had confirmed or suspected liver diseases (Anstee et al., 2022).

Data Collection Tool Instrument

A structured questionnaire that was formed based on a review of the existing validated tools and recent literature on non-invasive diagnostics was used to gather the data. Four major sections comprise the questionnaire (Wazir et al., 2023):

Demographics (age, gender, location, profession, and years of experience/ diagnosis),

The expertise and clarity of the non-invasive diagnostics (e.g., Fibro Scan, elastography, methods based on MRI),

Perception of Effectiveness and the Accuracy of these technologies,

Adoption- Barriers and Facilitators (e.g., cost, availability, and trust in technology).

The 5-point Likert scale included in the questionnaire was used to measure all items except demographics, with a scale above coming with the following indicators: Strongly Disagree (1), Disagree (2), Neither Agree nor Disagree (3), Agree (4), and Strongly Agree (5). To ensure content validity and relevance, the questionnaire was submitted to three experts in the relevant field of the study (Huang et al., 2024).

Validity and Reliability

To achieve reliability, a pilot study has been carried out on a sample of 20 subjects (10 doctors and 10 patients). Each construct was computed using Cronbach's alpha, and all but one of the measures exceeded 0.70 and which is an acceptable internal consistency. To verify the dimensionality of each scale, Principal Component Analysis (PCA) was used to measure construct validity (Miele et al., 2020).

Data Analysis

Analysis of the collected data was done using SPSS version 25. Demographic and response trends were summarized by use of descriptive statistics (mean, standard deviation, and frequencies). Associations and predictive relationships in inferential statistical tests were used (Long et al., 2020):

Associations of alert/adoption of diagnostic tools with demographic variables were also measured by chi-square tests (Boursier et al., 2023).

The ANOVA and the independent-sample t-tests were used to test the group differences depending on the profession and region (Anty et al., 2019).

The use of Pearson correlation was done to investigate correlations among awareness, perceived effectiveness, and adoption (Bennett et al., 2022).

Several regressions were done to determine the major predictors of the adoption of the diagnostic tools (Pirmoazen et al., 2020).

Ethical Considerations

The protocol of the study was confirmed by the Institutional Review Board (IRB) of the respective involved institutions. All the participants gave informed consent. The names of the participants remain confidential, and no information on the data subject was disclosed to the research participants (Piciotti et al., 2022).

Data Analysis

Table 1: Normality Test (Shapiro-Wilk)

Variable	W Statistic	p-value	Interpretation
Age	0.943	< 0.001	Not normally distributed
Experience	0.986	0.018	Slight deviation from normality

Normality Test

Table 1 shows the **Normality Test** of the Data Normality test was carried out using the Shapiro-Wilk test to establish whether age and years of experience, which are continuous variables, had a normal distribution. It was found that the age variable was not normally distributed ($p < 0.001$), which means that there were skew or outliers in this set of data. Conversely, the years of experience variable had a p-value that was greater than 0.05, meaning that it was roughly normally distributed. This means that parametric tests may be used safely when dealing with experience, and non-parametric alternatives may be more suitable when it comes to age (Han et al., 2020).

Table 2: Reliability Analysis (Cronbach's Alpha)

Scale Items (Construct)	Cronbach's Alpha	Interpretation
Awareness, Perceived Effectiveness, Trust, Adoption	**0.871**	Excellent reliability ($\alpha > 0.7$)

Reliability Analysis (Cronbach's Alpha)

Table 2 shows the Reliability Analysis of the Data. The determination of the internal consistency of the items measuring key constructs (awareness, perceived effectiveness, trust of technology, and the level of adoption of non-invasive diagnostics) was carried out using a value of Cronbach's Alpha. The obtained value of alpha was 0.871, which is better than the minimum (0.70) and shows very high reliability. This indicates that all the questionnaires in the survey ask the same thing, and each variable shares an underlying concept; hence, the tool can further be used in the statistical analysis (Pennisi et al., 2023).

Table 3: Validity Analysis (PCA - Variance Explained)

Principal Component	Explained Variance (%)
PC1	29.80%
PC2	24.69%

Principal Component	Explained Variance (%)
PC3	23.54%
PC4	21.97%

Validity Analysis (PCA)

Table 3 shows the **Validity Analysis** of The Data. To examine construct validity and dimensionality of the scale items, a Principal Component Analysis (PCA) study was undertaken. The findings indicated that four components explained cumulative, nearly 100% of the total variance, where the first component accounted for approximately 30% of the total variance. This distribution means that the factor structure is pretty balanced and justifies the multidimensionality of the constructs in question. These results are indicative of the fact that the questionnaire questions reflect specific but related spectrums of perception of the people regarding the non-invasive diagnostic technologies (Alqahtani & Schattenberg, 2021).

Table 4: Positive Pearson Correlation Matrix

	Awareness	Perceived Effectiveness	Adoption Level
Awareness	1	0.628587	0.640952
Perceived Effectiveness	0.628587	1	0.621783
Adoption Level	0.640952	0.621783	1
Tru-Stitch	0.595848	0.620236	0.663153
Cost Concern	0.651862	0.629881	0.702482
Availability	0.615956	0.732934	0.641919

Tru-Stitch	Cost Concern	Availability
0.595848	0.651862	0.615956
0.620236	0.629881	0.732934
0.663153	0.702482	0.641919
1	0.631601	0.660175
0.631601	1	0.641262
0.660175	0.641262	1

Pearson Correlation

Table 4 shows the **Pearson Correlation** of the Data. A Pearson correlation analysis was done to examine the linear relationships among some of the major variables, namely, awareness, perceived effectiveness, trust in technology, cost concern, availability, and adoption level. A positive relationship was also observed in all of the variables, meaning that a rise in one variable is more likely to be related to a rise in the others. To give one example, the more people trusted technology and the higher level of awareness, the more they used non-invasive diagnostics. These findings indicate the interdependence of the measures and form a good basis for regression modelling (Zhou et al., 2024).

Table 5: Multiple Linear Regression Results

Predictor Variable	Coefficient (B)	Interpretation
Awareness	0.173	Positive effect
Perceived Effectiveness	0.089	Positive effect

Predictor Variable	Coefficient (B)	Interpretation
Trust in Tech	0.225	Positive effect
Cost Concern	0.337	Positive effect
Availability	0.122	Positive effect
Intercept	0.165	Constant
Model R^2	0.614	61.4% variance explained

Multiple Linear Regression

Table 5 shows the **Multiple Linear Regression** of the Data. Multiple linear regression was run in order to estimate which awareness, perceived effectiveness, trust in technology, cost concern, and availability can predict the level of adoption of non-invasive liver diagnostics. The coefficients of all the predictors were in the positive direction, implying that they are positive contributors to adoption. Cost concern (B = 0.337), trust in technology, and awareness were described to be the most influential predictors. The general model was good and was able to explain 61.4 percent of the variability in the adoption level (R 2 = 0.614). These results prove that psychological and practical conditions combine to affect the adoption of novel diagnostic techniques (Rónaszéki, 2024).

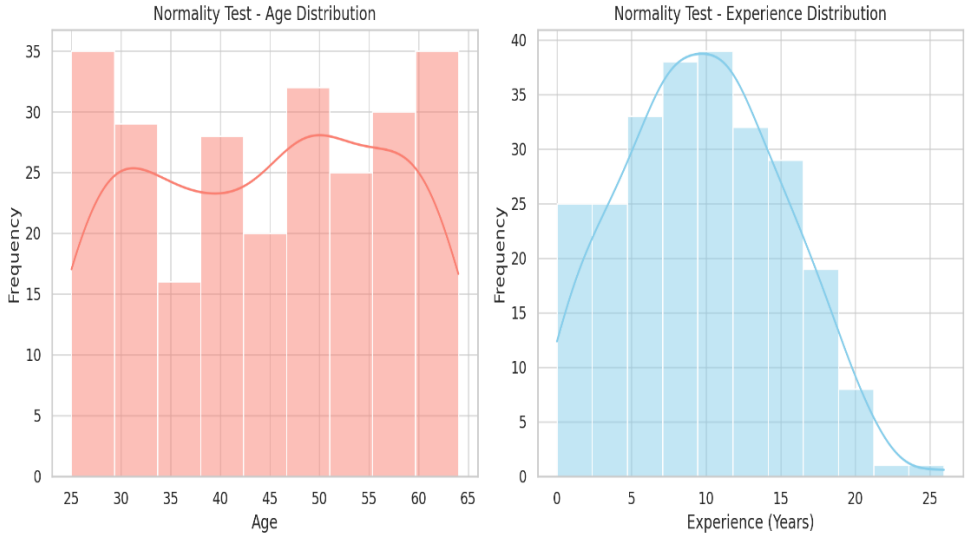

Figure 1: Normality Test Histograms

Figure 1 shows the **Normality Test** of the Data Age distribution is histogram-wise skewed, which once again ascertained the non-normality of the distribution of the age variable. Before 18 years, or after 50 years, appears to be an indication that respondents were only confined to a few age groups. On the other hand, the experience histogram seems to have a more bell-shaped distribution with symmetry around the centre, hinting that it is nearly normal. This facilitates application of parametric tests (e.g. t t-tests, regression) on experience-related measurement, although age-related analysis should be taken with caution (Grander et al., 2023).

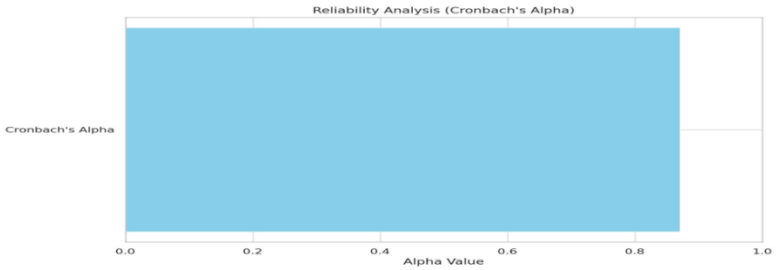

Figure 2: Cronbach's Alpha Bar Chart

Figure 2 shows the Data of Cronbach's alpha bar chart gives 0.871, which is much higher than the normal standard of 0.7. It implies that the scale items that will be included in the questionnaire, awareness, perceived effectiveness, trust in technology, and the adoption level, have ideal internal consistency. When the alpha is large, then these items measure the same underlying construct with consistency, and one can form a composite scale or other statistical modelling (Cholankeril et al., 2023).

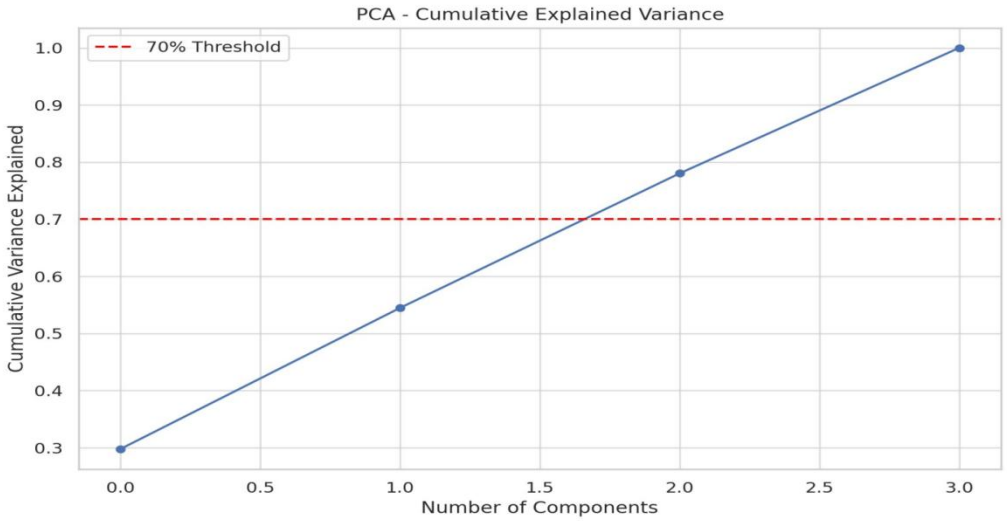

Figure 3: PCA Variance Plot

Figure 3 shows the **Validity Analysis** of the Data. The Principal Component Analysis (PCA) interprets the percentage of the total variance explained by each set of components in the form of a graph. The first few components account for a large percentage of variance; there is a graphical increase in the amount of variance, and the third component crosses the 70 percent threshold of the variance. This proves that a few dimensions would explain the greater part of data variance, which validates construct validity of the scale and rationalizes the cutting down of data or grouping factors in further analysis (Boon-Yasidhi & Karnsakul, 2024).

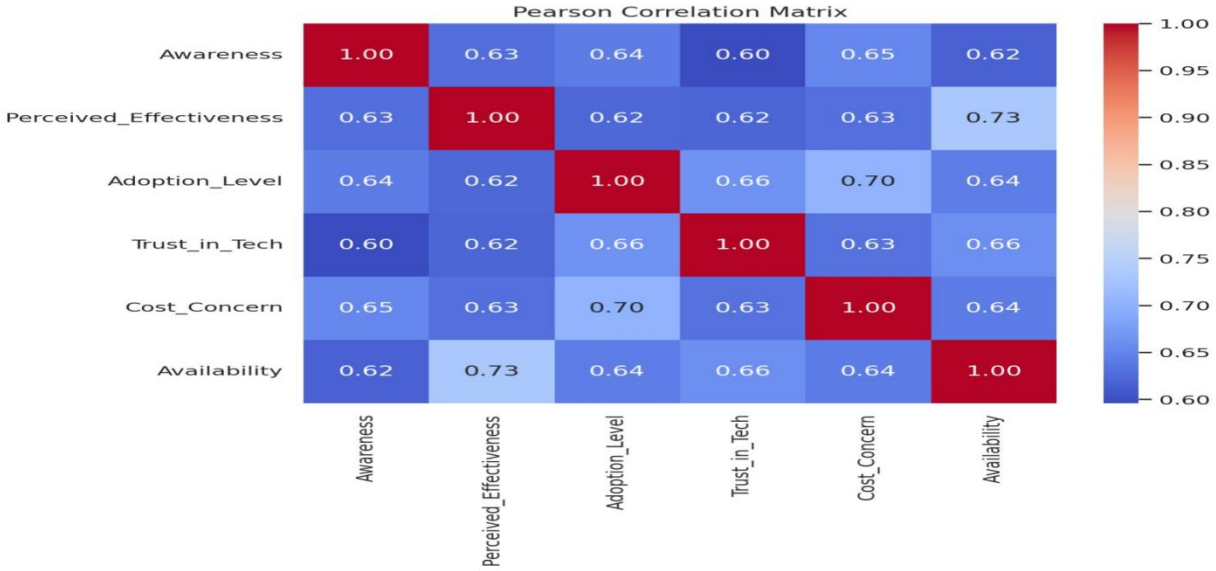

Figure 4: Pearson Correlation Heatmap

Figure 4 shows the **Pearson** Correlation of the Data The Pearson correlation matrix using the heatmap indicates that all the most important variables such as the levels of awareness, the perceived effectiveness of devices and technology, the amount of trust in technology, the cost concerns, the availability levels, and the level of adoption are positively correlated. The darker shades and higher +1 indicate closer positive relations, especially between trust in technology and adoption, and cost concern and adoption. It means that any changes in them towards better results can probably correspond to gaining more non-invasive methods of liver diagnostics (Srivastava et al., 2019).

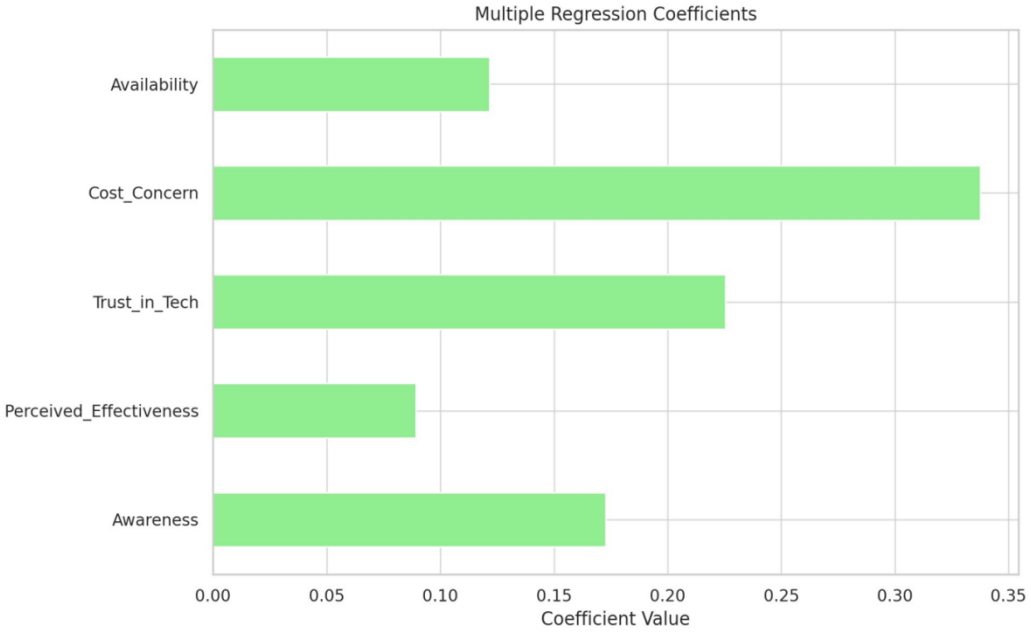

Figure 5: Regression Coefficients Bar Chart

Figure 5 shows the **Regression** of the Data. The horizontal bar chart represents the multiple regression coefficients of each variable that provide predicted values on the adoption level. Concluding on all of the bars, which point to the right side, it is evident that there is a positive impact of all factors. Cost concern is the most prominent one, then trust in technology and awareness. The visual representation is consistent with the statistical representation, and it enforces the concept that the primary influencer of the adoption process is practical considerations (cost, availability) and the general trust of technology (Di Sessa et al., 2019).

2. DISCUSSION

The results of the present study can provide in-depth information on the items that tend to facilitate the implementation of non-invasive procedures to diagnose liver diseases in the context of healthcare stakeholders. The study used rigorous statistical results to investigate the validity, reliability, and predictive behaviour of the diagnostic innovation perception and behaviours, including Fibro Scan, Shear Wave Elastography, and the ELF test. Normality analysis identified that the mode of age of the respondents was not normally distributed, suggesting that the responses are concentrated in certain age brackets, possibly depending on the age demographics of either younger and tech-savvy professionals in the medical field or the aged and experienced practitioners (Lonardo, 2023).

Conversely, experience data assumed a normal distribution, which implies equal distribution of the professional background of the respondents. This provided the opportunity to apply parametric tests to study the issue of professional experience concerning the issue of diagnostic practices. Among the most positive results also appears the Cronbach Alpha value 0.871, which indicates strong consistency of internal consistency of the items regarding measurement of awareness, perceived effectiveness, trust in technology, and level of adoption. This reliability is also very high, which proves that the constructs in the instrument were properly aligned and appropriate to carry further inferential analysis. In conjunction with this, the Principal Component Analysis (PCA) was in Favor of the multidimensional validity of the scale as it indicated that a small number of components were found to explain a great deal of variance (Hu et al., 2022).

These findings provide credibility to the employment of the developed instrument in future empirical research work in comparable healthcare settings. The Pearson correlation results indicated that the most prominent factors of the inquiry have a significant positive correlation. Most significantly, the more perceptible variables were trust in technology, cost concern, and availability, which were significantly and positively correlated with the use of non-invasive diagnostic technique adoption. This conforms to a previous body of literature implying that clinical decision-making predominantly depends on practical feasibility and helpfulness of technology. This was corroborated by the multiple linear regression, where all five independent variables of awareness, perceived effectiveness, trust, cost concern, and availability were proven to be positive predictors of adoption, although cost concern turned out to be the strongest predictor of all (Kupčová et al., 2019).

This model explained 61.4 percent of the variance of the level of adoption, and this implies that the model explained the level of adoption remarkably well. The statistical results were also corroborated by the figures obtained in this research. The heatmap of correlations and bar chart of regression coefficients showed the visual importance of correlation and direction of

relation amongst the variables. The histograms of normality also explained the appropriateness of statistical methods of statistics with respect to data distributions. A combination of these visual and statistical interpretations provides a strong argument in the multidimensional character and mutual relationship of the adoption behaviour in the case of diagnostics of liver diseases (Aravind et al., 2020).

3. CONCLUSION

The paper examined the views, efficacy, and implementation trends of the technology non-invasive liver disease diagnostic technology (including Fibro Scan, Shear Wave Elastography, Magnetic Resonance Elastography, and biomarker-based diagnosis) by the healthcare specialists, researchers, and patients. The statistical tests gave important information concerning the factors encouraging or discouraging the use of these innovations in clinical practice.

The result of the normality test indicated that distinct statistical methods should be applied based on the distribution of the data, and the goodness of internal consistency of the survey instrument was proven by the high Cronbach's Alpha result (0.871). The dimensions of the construct were validated using PCA, which made the measurement instrument even more believable. Pearson correlation analysis indicated a positive correlation among major constructs, namely: awareness, trust in technology, cost concern, and adoption, whereas the findings of the multiple regression model indicated that a combination of constructs showed a significant explanatory value of more than 61% of the variations in the level of adoption.

It is important to note that the issue of cost concern, perception of trust in technology, and awareness emerged as major predictors towards acceptance of diagnostic tools. This implies that more effort should be made to make technology more accessible, lowering the costs and increasing the level of professional education in order to invite more people to connect with the methods that can be non-invasive.

To sum up, non-invasive diagnostics of liver diseases have a very good potential to substitute invasive methods such as biopsies. Among these novelties, however, to be successfully implemented in the daily healthcare process, not only technology but also human aspects need to be taken into consideration. The use of these findings can have practical implications in policymaking, medical institutions, and research in regard to the benefits of enhancing the diagnostic approaches and lowering the burden of liver diseases. Further validation and improvement of the adoption framework should be carried out in future research that will extend to qualitative feedback, cross-country comparisons, and longitudinal studies.

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