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Artificial Intelligence Augmentation in Blood Transfusion, Biochemistry, and Hematology of Digital Pathology: A Comparative Performance Evaluation on Pathology Labs and Corporate Hospitals located in Bengaluru

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***Abstract* — *Artificial intelligence augmentation is increasingly incorporated in the medical and healthcare sphere, especially in the pathology arena of Blood transfusion, Biochemistry, and Hematology, towards detecting and analyzing diseases and disorders. Hence, it is important to understand the implications of artificial intelligence on humanity with the pathology's innovation practices. The pathology laboratories and hospitals need to incorporate artificial intelligence into specific functions and sub-functions of result-oriented specialties to create effortless healthcare activities. This study was undertaken with selected pathology laboratories and healthcare organizations in Bengaluru that have access to digital initiatives and artificial intelligence into their business process for the last three years and examine the performance on three result-oriented functions in which artificial intelligence is incorporated. This article studies on the potential competencies of artificial intelligence augmentation and builds awareness in the healthcare sector on the capabilities of augmenting the right intelligent systems enables in streamlining the activities carried out in the pathology lab and exhibits that on what organization need and how technological advancement and innovation helps in improving the organizational performance and notifies that if the performance improvement measures are followed with continuous update and maintenance, only then innovations in healthcare result in success.*

Keywords — *Artificial Intelligence, Augmentation, Blood Transfusion, Biochemistry, Hematology, Pathology*

I. INTRODUCTION

Digital Pathology (DP) in healthcare is setting new dimensions in the healthcare market; coordinated programs designed to prevent, detect, and control healthcare-associated infections (HAIs) are focused heavily by health organizations. Artificial intelligence augmentation promotes innovative practices in the healthcare organization to detect illness and disorders, prevent errors, create transparency in the flow of activities, and encourage the potential of technologies in the workplace. AI augmentation in healthcare-associated dimensions leads to manage the doctor-patient ratio and reduce medical costs as found from the existing pool of studies carried out. The introduction of new technologies, in the absence of infrastructure to use them safely, may lead to adverse events. AI enables maximizing the patient outcomes on treatments and diagnosis and is part of the organizational responsibility to provide effective, efficient, and deliver quality health services. That must be achieved by collaborating with the technology service providers to build a modular and reliable AI-augmented intelligent system that assists pathologists and other healthcare professionals in managing and delivering patient care and handling human-centric tasks that are void and repetitive. Healthcare facilities must implement AI-based systems to enhance healthcare-related experiences. An overall approach to examine the performance of artificial intelligence (AI) enabled digital pathology at the healthcare facility is based upon Quality of Service, Access to Information and Training, Facilities, and Support services. Artificial Neural network-based deep learning has become an increasingly important machine learning technique in building the models to fight against security, illness detection, drug detection, and especially controlling the increasing resistance of errors in pathology. As many pathologists see a positive surface of (AI) in diagnostics. It is essential to incorporate the early sequence of prediction in mild and extreme illnesses, enabling hospitals and path labs to render the best and most accurate services.

Although (AI) is enabled in various healthcare demarcations, it is rarely found any research studies on its implicated towards the organization's performance. Inadvertent exposures to AI-enabled tools and systems have resulted in the Detection of mild illness with significant support of measures to take. Lack of adherence to established standards and guidance can result in adverse outcomes (AI) augmented solutions in healthcare facilities. The study was undertaken at the corporate chain of pathology labs and hospitals in Bengaluru to assess the following (AI) augmented practices in the demarcation of Blood Transfusion, Biochemistry, and Hematology for the last three years.

II. METHODOLOGY

The study was undertaken at Pathology laboratories and corporate hospitals located in Bengaluru. The different demarcations were observed through a structured close-ended checklist. The observation was carried out for three weeks. The pathology departments where AI-augmented was heavily incorporated were chosen: Blood Transfusion, Biochemistry, and Hematology. The structured checklist evaluated parameters like Probability of Contamination on the five-point scale where 1 is poor, 2 is Fair, 3 is Good, 4 is Very Good, and 5 is Excellent. The third parameter that was observed in the departments mentioned above in hospital and path labs are Directions on handling the Services, Directions on furnishing the Services, Access to Electronic Health Records, Reducing the errors, Streamlining the process of diagnosing diseases, Standard facilities available to use, Spot the Health and diseased state, Collection of tests offered, Spot functions of body organs and their mechanisms, Recognize the health condition and its effects, Quality of Pathology Images, Quality of Concluding reports, Level of clinical advice available, Quality of customization of treatments, Improvement in the efficiency of healthcare professionals, Level of information sharing, and Overall performance. The data analysis was carried out in SPSS version 20. The Statistical tools used were Percentage analysis, Correlation Analysis, One-Way ANOVA, and General Linear Model for assessing the performance of (AI) augmentation in the selected departments of pathology.

III. RESULT AND DISCUSSION

Table-I Descriptive statistics and Percentage Analysis of Demographic Profile

Descriptive Statistics

		Designation of the Respondent	Gender of the Respondent	Age of the Respondent	Experience of the Respondent
N	Valid	130	130	130	130
	Missing	0	0	0	0
Mean		1.8385	1.4231	2.2000	2.0462
Median		2.0000	1.0000	2.0000	2.0000
Mode		1.00	1.00	2.00	2.00
Std. Deviation		.97888	.49596	.84816	.80562
Variance		.958	.246	.719	.649
Sum		239.00	185.00	286.00	266.00
Percentiles	10	1.0000	1.0000	1.0000	1.0000
	25	1.0000	1.0000	2.0000	1.0000
	50	2.0000	1.0000	2.0000	2.0000
	75	2.0000	2.0000	3.0000	3.0000

A. Correlation Analysis

Factors influencing the state of artificial intelligence augmentation in digital pathology sphere of blood transfusion, biochemistry, and hematology:

The factors influencing the state of Artificial Intelligence augmentation in blood transfusion, biochemistry, and hematology divisions were measured with seventeen variables of performance evaluation that enhances the incorporation of AI systems in digital pathology. All the seventeen variables say about to what extent the state of AI augmentation practices are in place and are essential to the diagnostic centers and help them to sustain the industry 4.o technical know-how in the plethora of functions and specific sub-functions in the healthcare sector that enables organizations to boost their growth and enjoy a competitive advantage with the sustainable AI augmentation practices in place. The Likert five-point scaling technique scored the responses.

Table-II Descriptive statistics of Artificial intelligence augmentation in Blood transfusion, Biochemistry, and Hematology of Digital Pathology

Descriptive Statistics

	Mean	Std. Deviation	N
Designation of the Respondents	1.98	.822	130
AI Augmentation in Blood Transfusion (ABT)	3.88	.592	130
AI Augmentation in Biochemistry (ABC)	3.73	.445	130
AI Augmentation in Hematology (AHT)	3.53	.530	130

Designation and Artificial Intelligence Augmentation in Blood Transfusion

Null Hypothesis: There is no significant relationship between the independent variable designation and the factors influencing the state of AI augmentation in blood transfusion.

Table-III Correlation of Designation and Artificial Intelligence Augmentation in Blood transfusion

Correlations

		Designation of the Respondent	AI Augmentation in Blood Transfusion
Designation of the Respondent	Pearson Correlation	1	.081
	Sig. (2-tailed)		.072
	N	130	130
AI Augmentation in Blood Transfusion	Pearson Correlation	.081	1
	Sig. (2-tailed)	.072	
	N	130	130

Correlation is significant at the 0.05 level (2-tailed).

Designation and Artificial Intelligence Augmentation in Biochemistry

Null Hypothesis: There is no significant relationship between the independent variable designation and the factors influencing AI augmentation in biochemistry.

Table-IV Correlation of Designation and Artificial Intelligence Augmentation in Biochemistry

Correlations

		Designation of the Respondent	AI Augmentation in Biochemist
Designation of the Respondent	Pearson Correlation	1	.038
	Sig. (2-tailed)		.412
	N	130	130
AI Augmentation in Biochemistry	Pearson Correlation	.038	1
	Sig. (2-tailed)	.412	
	N	130	130

Correlation is significant at the 0.05 level (2-tailed).

Designation and Artificial Intelligence Augmentation in Hematology

Null Hypothesis: There is no significant relationship between the independent variable designation and the factors influencing the state of AI augmentation in hematology.

Table-V Correlation of Designation and Artificial Intelligence Augmentation in Hematology

Correlations

		Designation of the Respondent	AI Augmentation in Hematology
Designation of the Respondent	Pearson Correlation	1	.056
	Sig. (2-tailed)		.196
	N	130	130
AI Augmentation in Hematology	Pearson Correlation	.056	1
	Sig. (2-tailed)	.196	
	N	130	130

Correlation is significant at the 0.05 level (2-tailed)

It is observed from the analysis that there is no significant relationship between the designation of the respondents and the state of Artificial Intelligence augmentation in blood transfusion, biochemistry, and hematology of digital pathology. Therefore, the variables like designation are not related to dependent variables of Artificial Intelligence augmentation in blood transfusion, biochemistry, and hematology. Here when the respondents' designation working in the hospitals and diagnostic centers varies between a Pathologist, Physician, Health-Tech Professionals, and Other Healthcare Professionals. Artificial Intelligence augmentation does not vary based on the type of job. Therefore, the different variables of state of artificial intelligence augmentation such as Directions on handling the Services, Directions on furnishing the Services, Access to Electronic Health Records, Reducing the errors, Streamlining the process of diagnosing diseases, Standard facilities available to use, Spot the Health and diseased state, Collection of tests offered, Spot functions of body organs and their mechanisms, Recognize the health condition and its effects, Quality of Pathology Images, Quality of Concluding reports, Level of clinical advice available, Quality of customization of treatments, Improvement in the efficiency of healthcare professionals, Level of information sharing, and Overall performance, does not influence on the designation of employees which always remains good. Hence, the null hypothesis, designation, and Artificial Intelligence augmentation in blood transfusion, biochemistry, and hematology of digital pathology are accepted.

B. ANOVA Analysis

Effective artificial intelligence augmentation practices and their influence on the overall performance of the Hospitals and Diagnostic centers located in Bengaluru

Null Hypothesis: There is no significant difference between the overall performance and the independent variable factors influencing artificial intelligence augmentation in blood transfusion, biochemistry, and hematology.

Model Summary

Model	R	R Square	Adjusted R Square	Std. An error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.273[a]	.075	.053	.44142	.075	3.387	3	126	.020

a. Predictors: (Constant), AI Augmentation in Hematology (AHT), AI Augmentation in Biochemistry (ABC), AI Augmentation in Blood Transfusion (ABT)

ANOVA

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	1.980	3	.660	3.387	.020[b]
	Residual	24.551	126	.195		
	Total	26.531	129			

a. Dependent Variable: Overall Performance
b. Predictors: (Constant), AI Augmentation in Hematology (AHT), AI Augmentation in Biochemistry (ABC), AI Augmentation in Blood Transfusion (ABT)

It is observed from the analysis that there is no significant difference between the independent variable factors influencing the state of artificial intelligence augmentation in blood transfusion, biochemistry, and hematology and the dependent variable overall performance. Therefore, all the predictor variables such as accuracy of test results, integrity, reliability, error detection, usability, precision, diagnostic specificity, and sensitivity of finding the diseases and disorders are strongly related to independent variables, which always holds good. Hence, the null hypothesis, overall performance, and state of artificial intelligence augmentation in blood transfusion, biochemistry, and hematology are accepted'.

Collinearity Diagnostics

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions			
				(Constant)	AI Augmentation in Blood Transfusion (ABT)	AI Augmentation in Biochemistry (ABC)	AI Augmentation in Hematology (AHT)
	1	3.959	1.000	.00	.00	.00	.00
	2	.018	14.664	.01	.01	.32	.60
	3	.017	15.282	.01	.90	.08	.20
	4	.005	27.519	.98	.08	.60	.19

C. Linear Model Between-Subjects Factors

Coefficients

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	95.0% Confidence Interval for B Lower Bound	95.0% Confidence Interval for B Upper Bound	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	3.623	.453		7.992	.000	2.726	4.521		
	AI Augmentation in Blood Transfusion (ABT)	.065	.068	.085	.958	.340	-.069	.199	.942	1.061
	AI Augmentation in Biochemistry (ABC)	.155	.088	.152	1.772	.079	-.018	.329	.992	1.008
	AI Augmentation in Hematology (AHT)	-.191	.075	-.224	-2.545	.012	-.340	-.043	.949	1.053

a. Dependent Variable: Overall performance

		Value Label	N
AI Augmentation in Blood Transfusion (ABT)	2.00	Fair	5
	3.00	Good	16
	4.00	Very Good	98
	5.00	Excellent	11
AI Augmentation in Biochemistry (ABC)	3.00	Good	35
	4.00	Very Good	95
AI Augmentation in Hematology (AHT)	2.00	Fair	2
	3.00	Good	56
	4.00	Very Good	72

Estimated marginal Means for AI augmentation in Blood Transfusion

Estimates

Dependent Variable	AI Augmentation in Blood Transfusion (ABT)	Mean	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Overall performance of ABT	Fair	3.833[a]	.200	3.438	4.229
	Good	3.673[a]	.147	3.381	3.964
	Very Good	3.746[a]	.097	3.554	3.937
	Excellent	3.933[a]	.172	3.592	4.275
Overall performance ABC	Fair	3.500[a]	.195	3.114	3.886
	Good	3.750[a]	.144	3.465	4.035
	Very Good	3.778[a]	.095	3.590	3.965
	Excellent	3.667[a]	.168	3.333	4.000
Overall performance AHT	Fair	4.000[a]	.203	3.597	4.403
	Good	4.000[a]	.150	3.703	4.297
	Very Good	3.876[a]	.099	3.680	4.071
	Excellent	4.000[a]	.176	3.652	4.348

a. Based on modified population marginal mean.

Multivariate Tests

	Value	F	Hypothesis df	Error df	Sig.
Pillai's trace	.033	.426	9.000	348.000	.921
Wilks' lambda	.968	.421	9.000	277.597	.924
Hotelling's trace	.033	.416	9.000	338.000	.926
Roy's largest root	.023	.873[a]	3.000	116.000	.458

Each F tests the multivariate effect of AI Augmentation in Blood Transfusion (ABT). These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.
a. The statistic is an upper bound on F that yields a lower bound on the significance level.

Univariate Tests

Dependent Variable		Sum of Squares	df	Mean Square	F	Sig.
Overall performance	Contrast	.287	3	.096	.500	.683
	Error	22.173	116	.191		
Overall performance	Contrast	.326	3	.109	.596	.619
	Error	21.167	116	.182		
Overall performance	Contrast	.157	3	.052	.263	.852
	Error	23.016	116	.198		

The F tests the effect of AI Augmentation in Blood Transfusion (ABT). This test is based on the linearly independent pairwise comparisons among the estimated marginal means.

Estimated marginal means for AI augmentation in Biochemistry

Estimates

Dependent Variable	AI Augmentation in Biochemistry (ABC)	Mean	Std. Error	95% Confidence Interval	
				Lower Bound	Upper Bound
Overall performance	Good	3.612[a]	.118	3.377	3.846
	Very Good	3.870[a]	.090	3.691	4.048
Overall performance	Good	3.458[a]	.116	3.229	3.686
	Very Good	3.845[a]	.088	3.670	4.019
Overall performance	Good	3.935[a]	.120	3.696	4.174
	Very Good	3.967[a]	.092	3.785	4.149

a. Based on modified population marginal mean.

Multivariate Tests

	Value	F	Hypothesis df	Error df	Sig.
Pillai's trace	.089	3.704[a]	3.000	114.000	.014
Wilks' lambda	.911	3.704[a]	3.000	114.000	.014
Hotelling's trace	.097	3.704[a]	3.000	114.000	.014
Roy's largest root	.097	3.704[a]	3.000	114.000	.014

Each F tests the multivariate effect of AI Augmentation in Biochemistry (ABC). These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.
a. Exact statistic

Univariate Tests

Dependent Variable		Sum of Squares	df	Mean Square	F	Sig.
Overall performance	Contrast	.575	1	.575	3.011	.085
	Error	22.173	116	.191		
Overall performance	Contrast	1.296	1	1.296	7.101	.009
	Error	21.167	116	.182		
Overall performance	Contrast	.009	1	.009	.045	.833
	Error	23.016	116	.198		

The F tests the effect of AI Augmentation in Biochemistry (ABC). This test is based on the linearly independent pairwise comparisons among the estimated marginal means.

Estimated marginal means for AI augmentation in Hematology

Estimates

Dependent Variable	AI Augmentation in Hematology (AHT)	Mean	Std. Error	95% Confidence Interval	
				Lower Bound	Upper Bound
Overall performance	Fair	4.000[a]	.309	3.388	4.612
	Good	3.780[a]	.072	3.636	3.923
	Very Good	3.701[a]	.110	3.483	3.919
Overall performance	Fair	4.000[a]	.302	3.402	4.598
	Good	3.940[a]	.071	3.800	4.080
	Very Good	3.375[a]	.108	3.162	3.588
Overall performance	Fair	4.000[a]	.315	3.376	4.624
	Good	3.953[a]	.074	3.808	4.099
	Very Good	3.943[a]	.112	3.721	4.165

a. Based on modified population marginal mean.

Multivariate Tests

	Value	F	Hypothesis df	Error df	Sig.
Pillai's trace	.159	3.320	6.000	230.000	.004
Wilks' lambda	.841	3.432[a]	6.000	228.000	.003
Hotelling's trace	.188	3.543	6.000	226.000	.002
Roy's largest root	.184	7.067[b]	3.000	115.000	.000

Each F tests the multivariate effect of AI Augmentation in Hematology (AHT). These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.

a. Exact statistic

b. The statistic is an upper bound on F that yields a lower bound on the significance level.

Univariate Tests

Dependent Variable		Sum of Squares	df	Mean Square	F	Sig.
Overall performance	Contrast	.182	2	.091	.477	.622
	Error	22.173	116	.191		
Overall performance	Contrast	3.623	2	1.811	9.927	.000
	Error	21.167	116	.182		
Overall performance	Contrast	.006	2	.003	.015	.985
	Error	23.016	116	.198		

The F tests the effect of AI Augmentation in Hematology (AHT). This test is based on the linearly independent pairwise comparisons among the estimated marginal means.

Artificial Intelligence Augmentation in Digital Pathology is becoming more adhesive in today's healthcare scenario in the hospital for controlling the cross-infection polynomials among the patients and Detecting diseases and disorders of human health. This study is an empirical site describing the spreading and equity of controlling the infection and Detection in Blood transfusion, Biochemistry, and Hematology and measuring its performance on the comparative lens. The study reveals a high risk of Detection in blood transfusion and biochemistry over hematology, which is moderately significant in performance. And artificial intelligence augmentation in hematology shows greater response on factors such as accuracy of test results, the integrity of the system, reliability of results for assistance to healthcare practitioners, error detection and bug identification, usability and convenience, the precision of drugs for identified disorders, specificity of results and sensitive of findings are better over the incorporation in blood transfusion and biochemistry of the pathology section. Thus, organizations focus on augmenting strong AI solutions in blood transfusion and biochemistry divisions that enable Detection and control of infections, diseases, and disorders at a mild stage. Therefore, initial orientation on AI augmentation to all the designation of employees must be trained, so that AI-augmented tools and systems available for assisting the healthcare professionals at workplace irrespective of divisions of pathology for detecting the abnormalities and symptoms of the illness, decreasing the error and defects in the results that meet the standard benchmark of human cognition. If the AI augmentation procedures and practices are followed with continuous updates only, the hospitals and pathology laboratories can deliver a better quality of service and care and financial growth. Awareness about AI augmentation in pathology should also be developed among healthcare organizations and communities.

CONCLUSION

The Pathology Labs and Hospitals should focus on structured planning to augment artificial intelligence in the specific functions. Subfunctions of pathology must be reliable, consistent, accurate, valid, and meet the user's needs with more user friendly. The department that is not on stability improvements and fails to predict the blocks of cells and structures while augmenting the artificial intelligence-based systems is Biochemistry, resulting in the Estimate marginal means, multivariate analysis, and univariate analysis. Thus, it should improve on collecting relevant data to evaluate the real-time outcomes. The existing system used in pathology measures and detects the indications by consuming more time than the AI system and manual. The study revealed that the current AI-augmented tools and systems available for assisting the healthcare professionals and detecting the abnormalities of the patient health are good and meets the standard Level. If the AI augmentation procedures and practices are followed with continuous updates, the hospitals and pathology laboratories can achieve better Quality of service and care and financial growth. The awareness about AI augmentation in digital pathology should also be developed among healthcare organizations in terms of how it will help decrease the rate of errors and defects and identify the symptoms and infections at the mild stage so that it can be controlled simultaneously. This can be done by giving training Programs on standard requirements, guidance on implementation in other demarcations of pathology like Cellular Pathology, Immunology, laboratory genetics, and Microbiology that can be considered a gap and scope for future study.

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