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Perceptions and Challenges for AI in Healthcare Centres

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Abstract: Artificial intelligence (AI) is heralded as an approach that might augment or substitute for the limited processing power of the human brain of primary health care (PHC) professionals. However, there are concerns that AI-mediated decisions may be hard to validate and challenge, or may result in rogue decisions.

Aim: To assess awareness, implementation status, perceptions, and barriers related to artificial intelligence adoption in primary health care centres.

Objective: To form consensus about perceptions, issues, and challenges of AI in primary care.

Method: A three-round Delphi study was conducted. Round 1 explored experts' viewpoints on AI in PHC (n=20). Round 2 rated the appropriateness of statements arising from round one (n=12). The third round was an online panel discussion of findings (n=8) with the members of both the International Medical Informatics Association and the European Federation of Medical Informatics Primary Health Care Informatics Working Groups.

Keywords: Medical record systems, computerised - privacy - general practice - Delphi technique - Artificial Intelligence

1. INTRODUCTION

Health systems around the globe are under stress due to many socio-political factors. The delivery of health services using optimal resources without compromising patient safety is in demand more than ever before. The rise in ageing population with multiple chronic diseases together with the increase of healthcare spending worldwide are some of the key factors putting strain on healthcare systems [1]. Primary health care (PHC) to some extent can respond to these demands at both population and community levels [2]. PHC is rapidly evolving not only in terms of health policies but also technologically. The majority of PHC providers are now digitized and use health information systems as part of care provision. With the advances in computational and informatics technologies it is now possible to exploit these health information systems using Artificial intelligence (AI) concepts such as machine learning and deep learning [3] [4].

AI is not a new concept and has been around for more than 50 years, popularized in the 1980s and 1990s with the advent of neural networks. However, this trend did not last long mainly due to bottleneck in computational capabilities of hardware at the time. With the latest advances in Graphics Processing Units (GPUs), we can now

overcome these computational limitations allowing us to develop more efficient neural networks in the form of deep learning. Deep learning is a machine learning technique where the models are trained using artificial neural networks with many layers (sometimes around 1,000). Deep learning has demonstrated significant results in various non-health and health-related applications using computer vision and natural language processing [5] [6]. However, very few of health-related AI systems are actually incorporated into clinical practice [7].

In recent years, deep learning has been used in PHC. Abramoff et al. developed an AI system, approved by the Federal Drug Administration of USA, to detect diabetic retinopathy in PHC centres [8]. A similar AI system using deep learning was developed in 2016 for the same purpose – automated diagnosis of diabetic retinopathy [9]. The key limitations of these two specific systems included a need for external validation, integration into clinical workflow, and the attitudes of clinicians [10] [11]. AI systems based on deep learning and other similar machine learning techniques are heavily critiqued for their 'black-box' paradigm wherein some of the intrinsic estimations are not clinically interpretable in biological terms. Additionally, various ethical issues are observed in the application of AI in PHC. One such ethical issue is the risk of introducing bias. An AI system can incorporate the biases inherent to the training data set, and propagate them into the validation set [12]. Collective knowledge from clinicians might be able to avoid these biases and subsequently help making appropriate clinical decisions. Another ethical issue is that dependence on AI by clinicians might change the patient-clinician relationship dynamic.

The above-mentioned studies together with several others give us a glimpse into the future on how PHC can leverage AI. However, despite all the methodological and computational advances in AI, very few are translated into routine clinical practice. We believe the issues and challenges surrounding the use of AI in PHC are one of the key reasons. Additionally, there is significant variability of opinions on the use of AI in PHC among various stakeholders - clinicians, informaticians, AI researchers, and AI practitioners. In this context, the International Medical Informatics Association (IMIA) Primary Health Care Informatics Working Group undertook this Delphi study to seek consensus on the perceptions, issues, and challenges of AI in PHC.

AIM

To assess awareness, implementation status, perceptions, and barriers related to artificial intelligence adoption in primary health care centres.

2. METHODOLOGY

2.1. Study Design

This research used a Delphi consensus method, a structured communication technique for gathering expert opinion through repeated rounds of questionnaires and controlled feedback.

2.2. Data Collection Methods

Data were collected using a three-round Delphi process involving experts in primary health care and health informatics.

Round 1:

An open-ended questionnaire was used to gather expert opinions on the role, opportunities, risks, and challenges of AI in primary health care.

Round 2:

Statements derived from Round 1 responses were presented to participants, who rated their level of agreement using a structured questionnaire.

Round 3:

A virtual panel discussion was conducted to clarify disagreements, refine viewpoints, and establish consensus on key themes.

Participation in all rounds was voluntary, and responses were anonymized to reduce bias.

2.3. Data Analysis

Qualitative data from Round 1 were analyzed using thematic analysis to identify recurring themes and key concepts.

Quantitative data from Round 2 were analyzed using descriptive statistics, including frequencies and levels of agreement.

Findings from the final panel discussion were synthesized to finalize consensus statements and conclusions.

2.4. Ethical Considerations

Ethical principles such as voluntary participation, confidentiality, and informed consent were strictly followed. Participants were informed about the purpose of the study, and their identities were kept anonymous throughout the research process. Since the study involved expert opinions and did not include patient data, minimal ethical risk was involved.

3. RESULT

A total of 200 students took part in this with females (58.1%) and male of (41.9%). Age of the participants ranging from 18-25 years. In this study females were more likely to demonstrate perception in dissection room experiences than male. Significantly INTERNS showed greater familiarity with advanced applications than third year and final year students and interns.

	N	Minimu m	Maximu m	Mean	Std. Deviation
Age:	200	18	27	21.86	1.893

Gender

		Frequency	Percent
Valid	MALE FEMALE Total	65	32.5
		135	67.5
		200	100.0

Year of the study

		Frequency	Percent
Vali d	III BDS		
	IV BDS		
	INTER N	74	37.0
	Total	66	33.0
		60	30.0
		200	100.0

Distribution and comparison of responses based on gender:

Item	Response	Males		Females		Chi-Square value	P value
		n	%	n	%		
Q1	1	60	32.0	128	68.0	7.326	0.05*
	2	5	41.6	7	58.3		
Q2	1	15	13.2	25	18.5	10.378	0.016*
	2	17	34.9	41	30.3		
	3	20	35.7	29	21.4		
	4	8	15.8	9	6.6		
	5	5	13.9	31	22.9		
Q3	1	19	47.5	21	52.5	6.481	0.090
	2	23	48.5	35	51.5		
	3	8	63.9	30	36.1		
	4	15	65.9	49	34.1		
	5	0	0	0	0		
Q4	1	16	22.1	21	17.9	19.818	0.0001*
	2	15	30.5	22	19.5		
	3	11	14.7	65	37.6		
	4	21	33.5	24	20.5		
	5	2	2.4	03	6.5		
Q5	1	16	15.7	19	14.3	7.657	0.077
	2	29	46.3	34	24.8		
	3	12	14.8	53	35.8		
Q6	1	35	53.7	99	73.3	5.049	0.005*
	2	30	46.3	36	26.6		

	3	0	0	0	0		
Q7	1	18	17.1	21	22.9	9.489	0.07
	2	25	34.9	37	35.1		
	3	10	20.6	57	39.6		
	4	9	12.6	14	14.6		
	5	0	0	0	0		
Q8	1	25	40.6	25	20.5	10.167	0.07
	2	15	30.3	73	39.7		
	3	6	15.6	35	31.6		
	4	5	13.8	2	4.8		
	5	0	0	0	0		
Q9	1	34	52.3	80	59.2	1.211	0.05*
	2	20	30.7	26	19.2		
	3	09	13.8	29	21.4		
Q10	1	24	32.2	22	27.8	8.275	0.07
	2	29	40.4	19	25.6		
	3	7	18.6	66	31.7		
Q11	1	16	37.1	87	42.9	5.928	0.115
	2	24	41.2	20	20.8		
	3	10	11.1	15	15.6		
	4	10	11.1	13	13.2		
	5	0	0	0	0		
Q12	1	15	28.5	26	26.5	6.303	0.98
	2	16	29.3	22	20.7		
	3	21	44.9	33	25.1		
	4	13	25.7	54	41.5		
	5	0	0	0	0		
Q13	1	64	32.2	135	67.8	2.483	0.478
	2	1	100	0	0		
	3	0	0	0	0		
	4	0	0	0	0		
	5	0	0	0	0		

P≤0.05 is statistically significant

Distribution and comparison of responses based on year of the study:

Item	Response	III BDS		IV BDS		INTERN		Chi-Value	P-Value
		n	%	n	%	n	%		
Q1	1	70	37.2	63	33.5	55	29.2	16.114	0.04*
	2	4	33.3	3	25	5	41.6		
Q2	1	7	15.9	10	12.7	16	13.6	7.842	0797
	2	16	27.6	16	17.6	10	11.6		
	3	7	15.9	15	16.7	20	16.6		
	4	30	49.6	16	17.6	6	10.6		
	5	14	12.6	14	17.5	8	17.5		
Q3	1	6	15	6	15	6	15	11.192	0.513
	2	14	20.6	16	23.5	3	4.4		
	3	18	21.7	14	16.9	9	10.8		
	4	7	15.9	11	25	7	15.9		
	5	0	0	0	0	0	0		
Q4	1	6	15.8	6	15.8	14	10.5	17.051	0149
	2	16	16.2	11	29.7	17	12.7		

	3	24	26.7	25	36.7	25	21.5		
	4	16	27.7	12	30.1	4	3.6		
	5	10	12.7	12	21.6	10	16.7		
Q5	1	5	14.3	5	14.3	15	14.3	18.317	0.106
	2	15	23.8	17	27.6	23	44.8		
	3	35	48.6	22	37.8	13	13.9		
Q6	1	34	45.9	32	48.4	26	43.3	42.592	0.05*
	2	40	54.1	34	51.6	34	56.6		
	3	0	0	0	0	0	0		
Q7	1	13	26.1	19	28.4	11	22.4	19.802	0.071
	2	16	29.5	18	26.6	17	28.5		
	3	30	32.7	25	35.6	22	34.6		
	4	15	19.5	4	8.5	10	21.5		
	5	0	0	0	0	0	0		
Q8	1	6	12.6	9	18.9	9	18.6	15.579	0.211
	2	11	19.7	13	22.4	19	25.5		
	3	30	43.6	32	41.7	25	35.6		
	4	17	21.6	12	21.7	7	11.5		
	5	0	0	0	0	0	0		
Q9	1	38	51.3	20	30.3	21	35.0	22.714	0.030*
	2	12	16.2	21	31.8	23	38.3		
	3	24	32.4	25	37.8	16	26.6		
Q10	1	5	10.9	15	29.9	10	11.7	19.322	0.081
	2	10	20.8	12	25.5	23	46.2		
	3	35	41.6	25	37.6	17	26.8		
Q11	1	18	12.7	11	17.5	15	23.8	25.349	0.09
	2	8	16.3	41	42.4	35	46.1		
	3	26	34.6	8	23.4	4	10.5		
	4	22	32.9	6	12.5	6	12.5		
	5	0	0	0	0	0	0		
Q12	1	16	33.7	5	10.9	10	21.7	29.118	0.07
	2	10	28.5	17	13.6	14	17.4		
	3	17	34.1	31	33.6	25	35.3		
	4	23	35.7	18	23.5	11	17.5		
	5	0	0	0	0	0	0		
Q13	1	74	37.1	65	32.6	60	30.1	14.206	0.288
	2	0	0	1	100	0	0		
	3	0	0	0	0	0	0		
	4	0	0	0	0	0	0		
	5	0	0	0	0	0	0		

P≤0.05 is statistically significant

4. DISCUSSION

The participants suggest that AI has potential to improve primary health care but unsupervised machine learning is currently not sufficiently mature or robust to be confidently used without checks in place. They were mostly in agreement that advances in AI application in primary care can lead to improvement of managerial and clinical decisions and processes. The primary care community needs to be proactive and guide the ethical and rigorous development of AI applications so that they will be safe and effective in the workplace.

The most established use of AI in primary care reported is suggested to be predictive modelling 15 . This is likely to be because the respondents do not have substantial clinical experience with AI tools – their suggested use cases

may be more academic and non-clinical such as predictive modelling. Similarly, their responses to the statements are likely to be more academic.

Participants also agreed that formal processes need to be developed and Ethics Committees (or Institutional Risk Management Committees) be trained to assess the ethical processing of data in AI applications. Data governance committees should contribute the oversight of AI applications and have processes in place to monitor data processing in and outputs from AI applications for fidelity, bias, and quality. There was less agreement on whether AI applications should be focused on service provision or decision support or whether it was easier to support the managerial or clinical process. It was not agreed that AI applications should learn and adapt to clinician preferences or behaviour or the extent of the potential for harm to patients.

Implication of Findings

The clinical and informatics community need to establish the professional rules for the initial and on-going use of AI applications to support managerial or clinical practice. Specific legislation may be needed to address some of the more intractable issues such as the liability for "black box" approaches of AI or even the liability of the clinician as a learned intermediary.

There is an agreed need for regular scrutiny by users (e.g., clinicians and managers) because the accuracy, fidelity, or relevance of the output of AI is not guaranteed, the current training datasets for AI applications may not be representative of specific populations or of the underlying terminological system or data models, and there is a need for mechanisms to identify biases in unsupervised algorithms. Identification of biases should be followed up with "unlearning" processes that increase the accurate functionality of AI applications 16 17.

Caution is needed as it may be more difficult to assess the impact of AI-based applications on continuity and coordination of care.

5. CONCLUSIONS

PHC and informatics experts reported that AI has the potential to improve managerial and clinical decisions and processes. However, unsupervised machine learning is currently not sufficiently mature or robust to be used confidently without checks in place. The primary care informatics community needs to be proactive to guide the ethical and rigorous development of AI applications so that they will be safe and effective in the workplace.

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