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# AI in medicine: an introduction to the potential benefits and challenges, and why doctors need to be involved

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## Introduction

The term artificial intelligence (AI) describes machines that are designed to emulate human intelligence.<sup>1</sup> AI can be trained to perform tasks that humans would consider basic, such as reading or spellchecking, but recently we have seen AI take on increasingly complex tasks, from self-driving cars and robotics to the generation and understanding of natural language. One recent driver of the prominence of AI in the public consciousness has been the release of natural language models, such as ChatGPT, which are designed to understand and generate human-like text.

Clinically, AI has the potential to benefit health care but there are issues that would first need to be addressed. This article discusses scenarios in obstetrics and gynaecology, and wider medicine, where the application of AI has the potential to improve patient care. As part of this, it will briefly discuss the development of an AI model and how it operates through a cardiotocography (CTG) interpretation case study. It will explore some risks to the use of medical AI around safety, bias and liability. Finally, it argues the importance of clinician engagement in the development of AI, with a key role in advocating for patients and themselves, ensuring its optimal implementation into healthcare.

## Artificial intelligence in health care

AI in medicine is not new. Diagnostic programs appeared as early as the 1970s, such as the rudimentary AI 'MYCIN',

designed to assist physicians with the management of patients with bacterial infections.<sup>2</sup> MYCIN identified probable bacterial infections using factors such as a patient's symptoms and blood test results and recommended appropriate therapies, failing to see widespread adoption owing to technological limitations. However, AI in health care has also benefitted from the recent advancements and higher profile of the technology, illustrated by the frequent media coverage of the medical use of AI.<sup>3,4</sup> The areas of development in health care are vast, including medical imaging, genomics, telemedicine and surgery.

It is also important to remember the non-clinical roles AI can have in health care. AI can be used in medical education; for example, ChatGPT-based programmes are already available to help medical students practice history taking.<sup>5</sup> It is also being used in explorative research, such as in drug discovery to help identify promising candidates for real-life testing.<sup>6</sup> However, potentially the most significant impact AI may soon have is facilitating patients' access to, and control over, their own health data. Many emerging AI-driven technologies in health care are patient-facing and integrated into consumer products like wearables and apps, designed to monitor patients' vital signs or symptoms away from healthcare settings. While current data show a mixed reception from patients, this shift could empower patients to take more control over their health and may in future help facilitate truly personalised health care.<sup>7,8</sup>

Medical imaging is a key area of health care with a comprehensive literature base investigating the use of AI in various radiological specialties, with a particular interest

around cancer detection.<sup>9,10</sup> Applications primarily focus on image interpretation, appealing because of the increasing number of images being generated relative to a limited number of radiologists.<sup>11</sup> Preliminary evidence of the performance of AI in this area is promising, and in some cases, such as the interpretation of chest radiographs, there is even evidence suggesting AI can match or surpass humans.<sup>12</sup> AI can achieve this as it can be remarkably good at identifying patterns among large datasets and can ignore factors such as fatigue which contribute to human error. Additionally, AI can also assist with several non-diagnostic tasks, such as quality control of images.<sup>9</sup>

Another area of interest for the development of AI is medical triage. AI that could quickly and effectively triage patients has the potential to reduce the burden on clinical staff and make sure the right patients are seen first. AI triage systems for emergency departments are being explored, with one group exploring the effectiveness of AI using inputs such as patient age and gender, vital signs and presenting complaint to triage patients into critical, urgent and non-urgent categories.<sup>13</sup> Additionally, a good community-based triage AI could potentially prevent unnecessary visits altogether if incorporated into services such as 111 or put directly into patients' hands through telemedicine. Using AI-driven, app-based chatbots to have a conversation with patients and elucidate pertinent signs or symptoms for triage are already in development.<sup>14</sup> Other potential uses of AI in health care are described in Table 1.

## Artificial intelligence in obstetrics and gynaecology

There are numerous potential applications for AI in obstetrics and gynaecology, some of which are highlighted in Table 2. This section explores two case studies which represent examples of how AI could be used in obstetrics and gynaecology. In doing so, this section will attempt to outline the basics of how an AI works and is developed.

### Case 1: Cardiotocography interpretation

An important early step in the development of a new AI model is to identify and characterise a 'problem' that AI could assist with. One such area of interest in obstetrics could be CTG analysis, partly due to poor interobserver agreement with human interpretation.<sup>15,16</sup> AI could improve this by analysing a trace and classifying it as normal, suspicious or pathological.<sup>17</sup> Theoretical benefits include more consistent interpretation and more frequent or continuous monitoring.

To further characterise the problem, it is useful to try and anticipate problems which may arise during the development of an AI system. All AI relies on data, so it is important to consider the feasibility of collecting suitable data in real-world settings. As CTG monitoring is already often

**Table 1.** Areas where artificial intelligence could be applied to health care. Divided into those aimed towards doctors to help with clinical management; those aimed towards patients and designed to be used in the community; and areas of broader medicine that feed into patient care.

#### Potential areas of AI in medicine:

Clinician-facing	Patient-facing	Non-clinical
Diagnostic programs e.g. CTG interpretation	Symptom tracking e.g. in chronic disease control	Administrative tasks e.g. appointment scheduling
Treatment optimisation e.g. antibiotic selection	Pain management e.g. in neuropathic pain	Medical education e.g. virtual reality training
Image interpretation e.g. X-ray screening	Medical chatbots e.g. patient triage apps	Systematic review synthesis e.g. abstract screening
Robotic-assisted surgery	Telemedicine	Drug discovery

**Table 2.** Potential areas for artificial intelligence in obstetrics and gynaecology

#### Examples of use-cases for AI in obstetrics and gynaecology

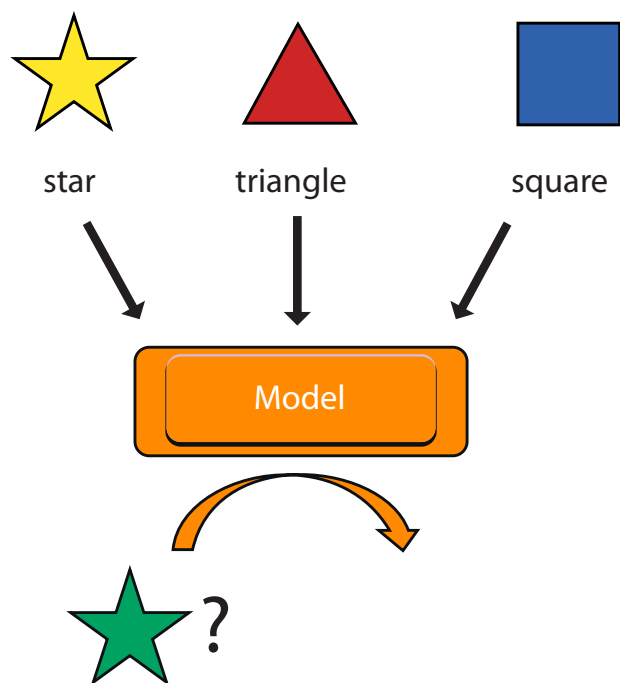
Obstetrics	Gynaecology
CTG interpretation	Endometriosis diagnosis
Ultrasound fetal age estimation & genetic screening	Computed tomography (CT) ovarian tumour detection
Ultrasound diagnosis of placenta accreta spectrum	Cervical cancer screening
Prediction of postpartum haemorrhage	Breast cancer therapy response analysis
Risk assessment for pre-eclampsia	Uroflowmetry interpretation

computerised, it would be relatively simple to feed this into an AI model. It is also worth reviewing what and how many input variables, or 'features', there are in the dataset, such as

heart rate variability and the number and length of decelerations in the case of CTG interpretation.

Another key consideration is how to evaluate a model's performance. One way that machines learn is through 'supervised learning', using datasets where each entry contains a descriptive human-assigned 'label'. By using labelled datasets these models can attempt to predict the label of new datapoints, an example of which is described in Figure 1. A model's performance can be calculated by comparing its predicted labels with the 'correct answers' of the human labels. In our CTG example, each trace in the dataset must first be categorised by a professional to allow the dataset to be used for supervised learning.

Next, developers must choose which AI algorithm to apply to the problem. Fundamentally, AI is applied mathematics, equations linking inputs to outputs, but the choice of algorithm will fundamentally determine how a model behaves. One of the potential algorithms suitable for this task is called k-nearest neighbours. First, the algorithm is trained on a dataset by learning all the features of each existing labelled trace. When asked to predict the label of a new datapoint, the algorithm compares it with all existing datapoints and the label which appears most frequently in the most similar existing datapoints is then assigned to the new



**Figure 1. An example of how a machine learning model can learn to differentiate between shapes using supervised learning.** The model is fed lots of examples of different shapes, each accompanied by a label describing what shape it is e.g. yellow star, red triangle, and blue square. The model is then presented with a new shape, the green star, and asked to predict the correct label from its options of star, triangle or square.

datapoint. Figure 2 shows a separate worked example using this algorithm.

In CTG interpretation our three classes are normal, suspicious and pathological. Therefore, if a new datapoint is surrounded by existing datapoints which are all labelled as the pathological class, then our algorithm would predict that the new datapoint also belongs to the pathological class. A k-nearest neighbours model has an accuracy of just under 90% on this task, suggesting that it would categorise a CTG trace into the same class as a professional roughly 9 out of 10 times.<sup>17</sup>

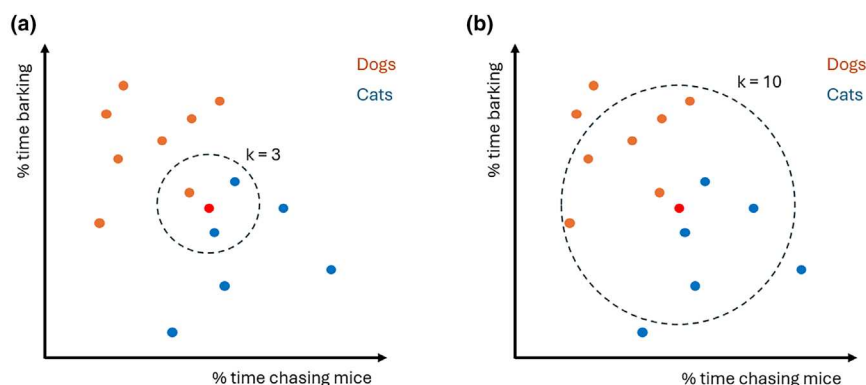
One real world application of this algorithm is in continuous CTG monitoring. A CTG-monitoring AI could observe wards of patients in real-time, facilitating early detection of fetal distress, warning clinical staff and improving patient outcomes. While some clinical studies testing this kind of system, such as the INFANT trial,<sup>18</sup> did not find a clinical benefit it will be interesting to see if the future use of more sophisticated AI models will result in improved outcomes.

### Case 2: Endometriosis diagnosis

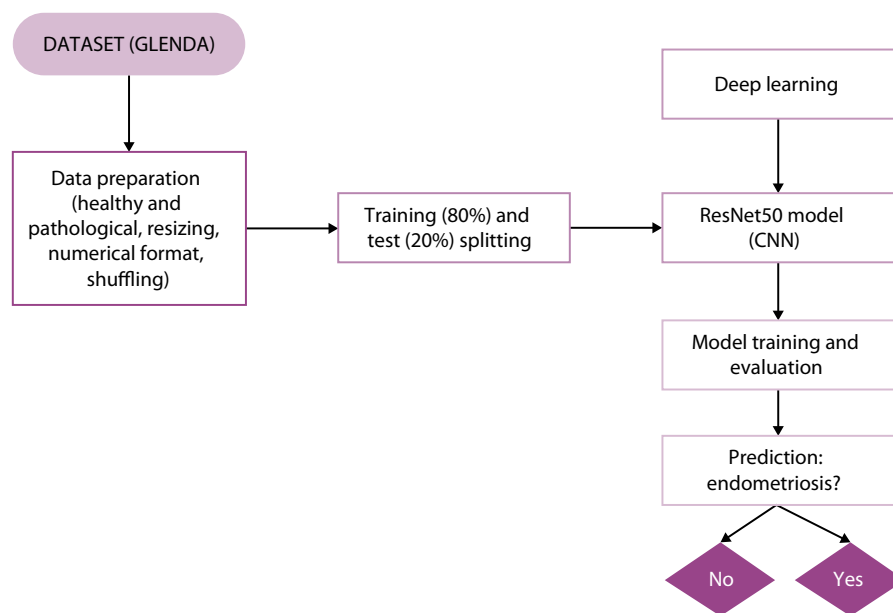
A potential application of AI in gynaecology is in supporting the laparoscopic diagnosis of endometriosis. Laparoscopy's reliability and accuracy are highly influenced by a clinician's expertise, lesion appearance, accessibility and interobserver variation.<sup>19</sup> Because of this, laparoscopic visualisations often need to be supported with histopathological analysis for an accurate diagnosis.<sup>20</sup>

An AI could potentially support clinicians to improve the accuracy of laparoscopic diagnosis. For example, researchers have developed an assistive classification system for the recognition of endometriosis using deep learning.<sup>21</sup> Deep learning AI uses 'artificial neural networks', which are models that emulate the structure of the brain with multiple layers of 'neurons' connecting inputs to outputs. While powerful, these models are often described as black boxes as it is very difficult to understand exactly what each neuron does and how it contributes to the output.

This deep learning AI uses images from the Gynaecologic Laparoscopy ENdometriosis DATaset (GLENDA) that were separated into two folders containing healthy (n = 2157) and pathological images (n = 2291) (Figure 3). Images were resized, labelled and mapped with 80% used for training and 20% for validation of the model. Researchers used a pre-existing model called Resnet50 which was trained on the GLEDNA images with the aim of recognising the presence or absence of endometriosis on laparoscopic images. The model benefitted from 'transfer learning', meaning that the performance of the model on this task improved because the model had already been pre-trained and familiarised with similar classification tasks.<sup>22</sup> With this model, researchers were able to diagnose endometriosis with 99% accuracy, which has the potential to increase the reliability of laparoscopy for the diagnosis of endometriosis, mitigating



**Figure 2.** An example of a **k-nearest neighbours algorithm** used to distinguish between cats and dogs. This algorithm has been trained on a dataset containing 14 datapoints representing 6 cats (blue) and 8 dogs (orange). Each datapoint is characterised by two variables, reflecting the percentage of time barking or chasing mice, graphed below. When given a new datapoint, represented by the red point, the algorithm predicts whether it is a dog or a cat based on the  $k$  closest existing datapoints, where  $k$  is a user-set number. When  $k = 3$ , the three closest points are 2 cats and 1 dog, therefore the algorithm would predict that the red datapoint is a cat. When  $k = 10$ , the ten nearest points are 6 dogs and 4 cats, therefore the algorithm would predict that the new datapoint is a dog. This example highlights the importance of the user-selected input, the value of  $k$ , to the output of this AI model.



**Figure 3.** A diagram based on Chrysa et al.'s methodology demonstrating how an AI was trained to support the laparoscopic diagnosis of endometriosis.<sup>21</sup> Images from the gynaecologic laparoscopy endometriosis dataset (GLENDA) were processed and fed into the pre-existing deep learning model ResNet50. After being trained on the endometriosis dataset, the ResNet50 model was able to predict endometriosis on laparoscopic imaging with a high accuracy.

issues of interobserver variability and reducing the need for histopathological analysis.

## Benefits and challenges of artificial intelligence in health care

AI has the potential to bring a range of benefits to health care, summarised in Table 3. However, it is important to ensure it is

used to support, rather than replace, healthcare staff, to ensure high standards of patient care.<sup>23</sup> Complex tasks, such as patient management, should continue to be led by clinicians while AI can initially focus on lower risk, high-reward tasks such as writing discharge summaries, a task which can take up a lot of clinical time and doctors may perform poorly on.<sup>24,25</sup>

Despite its potential benefits, there are questions we must ask as AI expands in health care. Most importantly: is it safe

**Table 3.** Benefits artificial intelligence could bring to health care**Potential benefits of AI in medicine**

To patients	To clinicians	To systems
Earlier disease detection	Workload reduction	Increased capacity
Personalised treatment plans	Increased time for training	Reduced costs
Greater insight into own health data	Decision support	Enhanced medical research

for our patients? An AI model is only as good as the data it is trained on. Biases in these datasets can be inherited by AI, resulting in a biased algorithm and poorer performance in certain patient groups. The majority of research is done with people from a Western, educated, industrialised, rich and democratic (WEIRD) demographic.<sup>26</sup> This demographic is therefore likely to be overrepresented in datasets available for AI training, potentially meaning that healthcare AI is only effective for this subset of the population. While doctors aren't without bias themselves, encoding this within AI risks worsening existing healthcare inequalities.<sup>27</sup>

Another risk to patient safety comes from the lack of explainability of some AI algorithms. As discussed, deep learning models perform better on complex tasks at the cost of explainability, effectively making them a black box.<sup>28</sup> There is also the question of who is responsible if an AI is wrong. Current legal frameworks around medical liability do not adequately consider stakeholders outside the core clinical team who may be increasingly influential over patient care, such as AI developers or AI models themselves.<sup>29,30</sup> There is therefore the risk that AI-related adverse outcomes may result in legal repercussions for clinicians or a loss of public trust in healthcare providers. In these early stages it is important to not only consider these issues but also how they may be mitigated, examples of which are outlined in Table 4.

### The importance of doctors during the emergence of healthcare artificial intelligence

Doctors play a crucial role in protecting the safety of patients, and their clinical expertise can help assess the validity of AI and identify potential errors before they cause harm. Doctors must act as advocates for their patients, making sure that incoming technologies are used in a way that will benefit patient care. The breadth of their training means doctors are

**Table 4.** Challenges to using AI in medicine and how these may be mitigated**Potential obstacles to using AI in medicine**

Obstacle	Mitigation
Dataset bias	Increasing diversity and representation in datasets
Black-box algorithms	Pushing for the use of more explainable algorithms
Privacy and security of health data	Calling for more regulation and resources to protect patients' data
Lack of understanding in workforce	Workforce education and training
Accountability of AI decisions	Careful deployment of AI with sufficient clinical oversight
Clinician and patient trust	Building up high-quality evidence of AI in medicine

well placed to promote the ethical use of AI by considering factors such as the impact of bias on patients, or the importance of maintaining patient confidentiality by protecting health data. In the future, patients may come to expect doctors to understand and analyse AI technologies on their behalf. The ability of the profession to adapt to this new technology will likely influence the speed by which real patient benefit can be seen.

Additionally, doctors can bring a valuable real-world perspective to the development of AI, helping to guide the direction of AI in health care. To achieve this, we are going to need doctors with a knowledge of both medicine and AI, who can have a comprehensive understanding of how these machine learning models work and predict where they can be best used. These individuals include clinical researchers, medical educationalists and doctors in industry who can bridge the gap between developers and frontline staff, helping to provide clinical oversight and build trust among clinical staff. AI in health care needs to incorporate medical professionals at all levels of training, generating doctors proficient in both fields, and developing the expertise to move this field forward in a safe, efficient, impactful and sustainable way.

The greatest barrier to doctors meaningfully engaging with AI is a lack of training and educational opportunities that currently exist. While it is possible to incorporate this into postgraduate training, and this will likely become prominent

in specialties like radiology, this is complicated by the competing requirements placed on the qualified doctor, including the necessity of service provision. The best place to develop an understanding of how AI will interface with medicine is at medical school, beginning by re-examining existing curricula to assess which areas are likely to be affected by emerging medical AI.

## Conclusion

The development of AI has the potential to improve health care in the near future. We are already seeing the exponential growth of AI-driven healthcare tools with the pressure to translate these into clinical practice. It is imperative that healthcare staff understand the principles and potential of AI, and in doing so ensure this technology maximally benefits health care and patient wellbeing.

## Disclosure of interests

SJ is an Associate Editor for *The Obstetrician & Gynaecologist*. She was excluded from editorial decisions and had no involvement in the decision to publish. The other authors have no conflicts of interest.

## Contribution to authorship

RA researched, wrote and edited the article. VG researched and wrote the article. SJ instigated, wrote and edited the article. All authors approved the final version.

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