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COMMENTARY

The paper chase and the big data arms race

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Artificial intelligence (AI)—systems that program themselves to listen, think, predict, anticipate, prognose, diagnose, and RESPOND better than people—are the future of reproductive medicine. And yet… despite its decades-long prominence in other industries, AI has barely made an impact on the clinical practice of infertility medicine.

Typically, artificial intelligence (AI) systems are trained with many billions or millions of data points (think Google predicting the content you are searching for). In reproduction, the largest published data sets that have been used to train or validate various deep learning, machine learning, and neural network systems, fall in the 1000–10,000 range, for example;

AI for reproduction dataset available for download at www.repro-ai.org.
Bormann, C. et al. [1] (742 embryo images);
Kan- Tor, Y. et al. [2] (6200 time lapse videos);
Chavez-Badiola, A. et al. [3] (1231 embryo images);
VerMilyea, M. et al. [4] (8886 embryos);
Letterie, G. et. al. [5] (2,603 total cycles (1,853 autologous and 750 donor cycles));
Tran, D. et al. [6] (8836 embryos);
Blank, C. et al. [7] (1052 patients),
Chen, T. et al. [8] (171,239 images from 16,201 embryos),
Miyagi, Y. et al. [9] (5691 embryo images).

Why is that?

Over 2.5 million IVF cycles are performed annually, generating millions upon millions of individual data points. IVF is supposedly one of the best registered procedures in medicine, with global IVF registries spanning Europe, USA, Latina America, Japan, Africa, Canada, New Zealand, and Australia (Bart CJM Fauser, 2091). The International Committee Monitoring ART (ICMART) has summarized global IVF data (Dyer et al., 2016) based on existing registries from approximately 60 countries and 2500 centers (collectively representing approximately 4.5 million IVF cycles) spanning 2008–2010. However, huge data sinkholes exist. For example, the majority of IVF lab data is recorded on paper charts, many labs don't record any image data, outcome metrics are extremely variable, and the Asia Pacific region (where an estimated 400,000 (plus) cycles are performed annually) does not (yet) report outcome data to a national registry.

The development of AI systems that are widely applicable across ART clinics and protocols, AND geographies and populations is challenged by the quality, diversity, and volume of available data. Some countries do not allow PGT, some countries require the transfer of all available embryos, and many do not routinely perform elective single embryo transfers. Currently, much of the world's IVF data is stuck in paper charts, owned and sold by private IVF clinics, with images taken on different microscopes, and cropped any number of ways to remove patient data. The major AI publications in reproduction use data gathered from one to three study sites.

In reproduction, AI systems could solve some of the hardest problems in reproductive medicine, for example, the complex dialogue between endometrium and embryo and recurrent miscarriage, the physiological function of the uterus and disease states like endometriosis and adenomyosis, new therapeutic targets for biological and chronological ovarian ageing, preimplantation genetics to improve pregnancy outcome, and recurrent implantation failure. The development of AI systems for ART has thus far developed around areas where embryo images (2D or timelapse video) are available: embryo selection, prediction of ploidy, and live birth. An immediate problem that could be addressed in the near future by these systems is "non-invasive" genetic diagnosis, vastly reducing the number of abnormal embryos that are sent for further genetic testing and frozen at IVF clinics—drastically reducing costs, man-hours, and embryo storage problems.

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As an embryologist in the USA, I have hand-transcribed IVF cycle data (patient name, DOB, medical record number, and other demographics) from the "paper packet" of a single IVF cycle up to 7 times, from the "daily checks sheet" to the: chain of custody, clinical EMR, cryostorage inventory, dewar specimen log, statistics spreadsheet, research spreadsheet, and lastly, into the SART CORS system. Image data (if collected at all) is almost never connected to the IVF lab KPI data, which is almost never connected to the clinical data. At least 100 times a day, I wonder, shouldn't this be easier???

The industry is not ready to exploit artificial intelligence, mainly because data collection, storage, and use is an exact science… one that the messy and ephemeral science of creating and growing human embryos does not lend itself readily to. The tedious, low-value work of cleansing, normalizing, and wrangling data is essential to AI success. PGT results are inaccessible until culled from PDF documents, and pregnancy results may be bHCG levels, obtained from an in-house endocrinology machine or outside testing facilities. Embryo images are most often collected on microscope computers inside the IVF lab that are certainly not networked, and probably not even connected to the Internet. Many IVF labs still use an ultrasound style printer, and don't save the embryo images. "On the ground" at the clinic, how can a digital system replace processes the embryologist finds indispensable, such as peeling the plastic label off of a cryo device after an embryo is thawed, and sticking it into the cryostorage record to become an indelible piece of evidence in the chain of custody?

Half a dozen commercial entities are developing AI systems for ART, while private centers seem to be hiring computer scientists to develop AI systems for "in house" use, perhaps banking on a future competitive advantage or offering for their patients. For AI algorithms to be facilitated into the routine course of patient care, in an easy and automated fashion, is currently impossible for the majority of ART clinics that still use paper charts, and don't capture and store image data. Importantly, data management solutions to enrich AI systems past the paradigm of embryo selection are lacking. These data could be: patient demographics, clinical and lab key performance indicators (KPI) and other relevant data streams (ultrasound images and PGT results, competency assessments, endocrinology, microscope and incubator QC, room/environmental factors) or billing codes.

The role of medical coders has not yet been fully realized for the development of AI systems for ART. Medical coders analyze individual patient charts and translate complex information about diagnoses, treatments, medications, and more into alphanumeric codes. These codes are submitted to billing systems and health insurers for payment and reimbursement and play a critical role in patient care. Billing specialists represent an un-tapped well of knowledge; as they are responsible for the accurate assessment of charts, they could also enrich AI systems with medical knowledge that can improve the system's performance.

In general, there are unresolved concerns about electronic health records and privacy; whether individuals can opt out, who controls or can have access to data and when consent is required, how to protect data from unauthorized use or accidental loss, and use of "de-identified" data for ethically approved research. Some countries have out-lawed ART patient data from crossing international borders, further restricting large-scale data sharing.

AI systems need "big data" to achieve robustness. Public databases of validated images and videos from diverse sources are needed. The development of blockchain-based technologies (think cryptocurrency) for data sharing in ART promises to promote collaborative research and innovation while reducing the cost of AI validation and implementation, and allowing patient data to remain under the control of the clinic by passing only the algorithms back and forth between partners.

The big data arms race is not one that individual IVF clinics or countries seem destined to win while the "paper chase" is still being fought on the ground.

Declarations

Conflict of interest Founder of ART Compass, a laboratory information management system that collects image and text data and uses artificial intelligence.

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