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Applying artificial intelligence to big data in hepatopancreatic and biliary surgery: a scoping review

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Abstract

Aim: Artificial Intelligence (AI) and its applications in healthcare are rapidly developing. The healthcare industry generates ever-increasing volumes of data that should be used to improve patient care. This review aims to examine the use of AI and its applications in hepatopancreatic and biliary (HPB) surgery, highlighting studies leveraging large datasets.

Methods: A PRISMA-ScR compliant scoping review using Medline and Google Scholar databases was performed (5th August 2022). Studies focusing on the development and application of AI to HPB surgery were eligible for inclusion. We undertook a conceptual mapping exercise to identify key areas where AI is under active development for use in HPB surgery. We considered studies and concepts in the context of patient pathways - before surgery (including diagnostics), around the time of surgery (supporting interventions) and after surgery (including prognostication).

Results: 98 studies were included. Most studies were performed in China or the USA (n = 45). Liver surgery was the most common area studied (n = 51). Research into AI in HPB surgery has increased rapidly in recent years, with almost two-thirds published since 2019 (61/98). Of these studies, 11 have focused on using "big data" to develop and apply AI models. Nine of these studies came from the USA and nearly all focused on the application of Natural Language Processing. We identified several critical conceptual areas where AI is under active development, including improving preoperative optimization, image guidance and sensor fusion-assisted surgery, surgical planning and simulation, natural language processing of clinical reports for deep phenotyping and prediction, and image-based machine learning.

Conclusion: Applications of AI in HPB surgery primarily focus on image analysis and computer vision to address diagnostic and prognostic uncertainties. Virtual 3D and augmented reality models to support complex HPB interventions are also under active development and likely to be used in surgical planning and education. In addition, natural language processing may be helpful in the annotation and phenotyping of disease, leading to new scientific insights.

Keywords: Artificial Intelligence, big data, surgery, liver, pancreas, biliary

INTRODUCTION

Artificial Intelligence (AI) encompasses a range of computational approaches with the central aim of developing algorithms to process and interpret information. AI methods can be applied to various input data types ranging from tabular datasets and images to multimedia and text. Although termed "intelligence", these algorithms are in no sense conscious or able to employ "rational thought", but in most cases, reflect model parameters derived exclusively from input data. Within AI, there are three overlapping fields that arguably have the most potential for HPB surgery: machine learning (ML), computer vision (CV) and natural language processing (NLP). ML uses algorithms to learn, adapt, and draw inferences from patterns in training data. CV allows for supervised or unsupervised image analysis, allowing for features of interest in images to be identified and characterized. For text-based sources of data written as prose or in a "human-readable" format (e.g., radiology or pathology reports), NLP allows computers to interpret human text or spoken language communication[1-5].

The specific areas and applications of AI most likely to deliver a positive impact on patient care currently need to be clarified, as are the barriers limiting the uptake of AI approaches into clinical practice. In 2021 Bari *et al.* described the applications of AI in hepatopancreatic and biliary (HPB) surgery, proposing the framework of preoperative, intraoperative, and postoperative AI applications. We have adopted this structure for this review[6].

With the increased availability of structured and unstructured healthcare datasets, the opportunity for AI-based approaches widens. Policymakers, healthcare providers, and industry are exploring new AI approaches, seeking to utilize data across a range of applications, including improving outcomes, optimizing the patient experience, and providing cost-effectiveness in delivering care at the health system level[7-9]. In this review, we aim to outline the fundamental AI approaches to pressing questions in HPB surgery, identifying where AI is most likely to have an impact in future patient care.

METHODS

This scoping review was performed in accordance with the PRISMA-ScR guidelines for scoping reviews[10]. The Medline database was searched systematically using the following Medical Subject Headings (MeSH) search terms to ensure the identification of appropriate articles; "Algorithms.mp. or algorithm/" AND "surgery/ or biliary tract surgery/ or liver surgery/ or pancreas surgery/". Articles were limited to English language and those published from 2012 onwards to provide contemporary studies that were likely reflective of current approaches in AI. Further supplementary searches were performed using citation lists and the Google Scholar database. The last search was conducted on 5th August 2022.

We defined "HPB surgery", as the surgical management of benign and malignant diseases of the liver, pancreas, gallbladder, and bile ducts. "Artificial intelligence" refers to the use of various algorithmic methods which could be applied to interpret or process information. We further assessed the identified papers for the element of AI primarily used i.e., machine/deep learning, computer vision or natural language processing[1-5].

Following the literature search, article titles and abstracts were screened by three reviewers (KMcG, SRK, JL) and those meeting the inclusion criteria underwent full-text review. Any disagreements were resolved by consensus within the group. References from included articles were searched to identify any other relevant articles. Conference abstracts were screened to assist in identifying related full-text articles before inclusion. Where more than one article was published from a single data set, the article analyzing the largest cohort of patients was included.

Data were extracted independently using a standardized *pro forma*. This included the aim of the study, methodology, year of publication, countries represented, the primary organ of focus, AI methods employed, and the number of patients (where applicable). Identified publications were further interrogated to find a shared focus on diagnostics, prognostics, or intervention, allowing further subdivision of the presented research. We then undertook a conceptual mapping exercise to identify areas of crucial importance.

We used a pragmatic approach to further select studies with a sample size equal to or greater than five thousand that satisfied the "velocity, volume and variety" of data points needed to be considered as "big data". A similar approach used previously, albeit with smaller datasets, acted as a benchmark[7-9,11]. Any disagreements on the selection of these papers were resolved by group consensus.

The Covidence online toolkit was used throughout the data collection and extraction stages of this scoping review[12].

RESULTS

Scoping search results

The search identified 5,221 articles, of which 134 were fully assessed for eligibility. A further 63 articles were identified from article citation lists or by the supplementary search of the Google Scholar database [Figure 1]. Following assessment, 98 studies[13-110] were included in this review, with most studies excluded due to being in conference abstract form only (n = 84).

Characteristics of included studies

Identified studies had a wide geographical distribution, coming from a total of 24 countries, with the majority from China or the USA (45/98). No papers identified originated from the African continent [Figure 2]. Studies on the use of AI in surgical conditions of the liver predominated (n = 51). Research on pancreatic and biliary conditions (n = 23) was included at a comparable frequency to one another. We noted a rapid increase in the number of studies published over the past three years, with almost two-thirds of the identified papers (n = 61) published since 2019 [Figure 3].

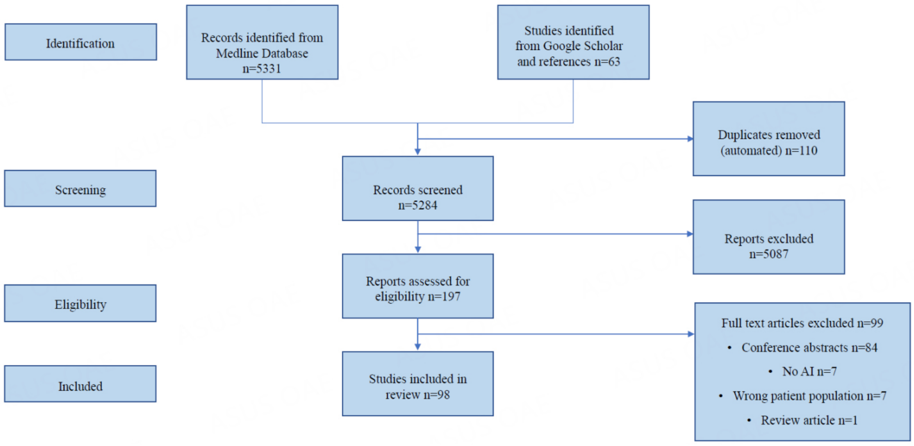

Figure 1. PRISMA flow chart detailing study selection and exclusion.

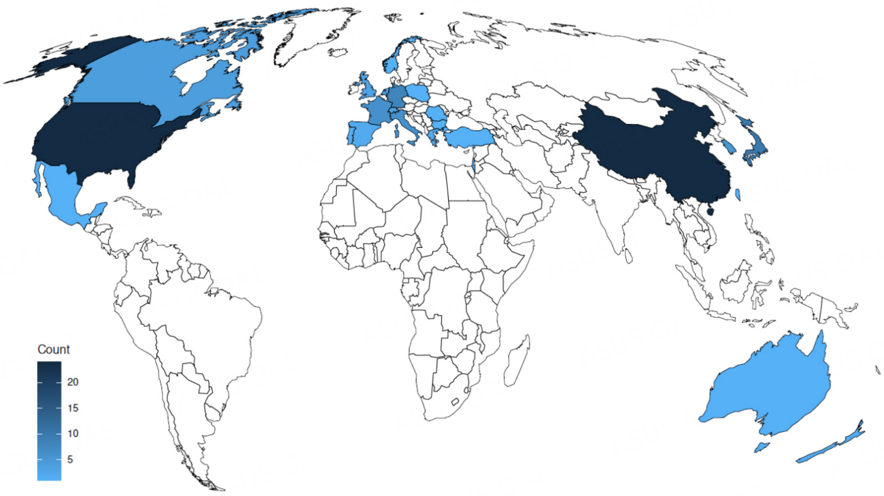

Figure 2. Global distribution of studies on the use of AI in HPB Surgery.

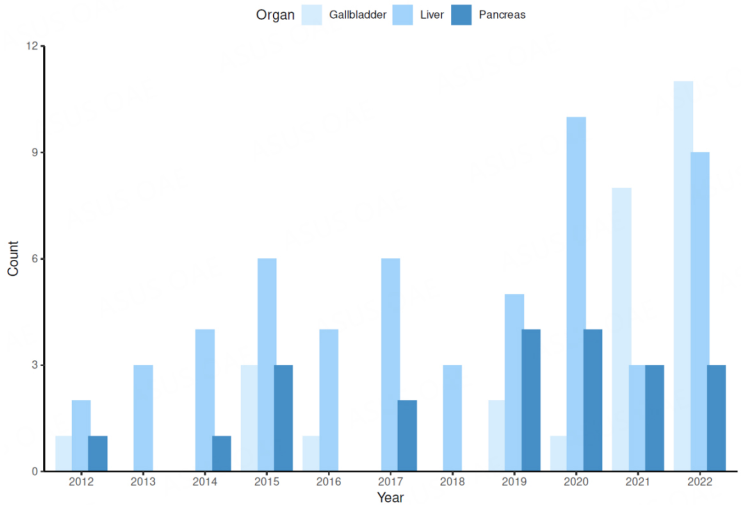

Figure 3. Primary organ of interest over time demonstrating the increase in frequency of publication.

Studies identified were subdivided into groups focusing on diagnostics, prognostics, and interventions. We assessed 23 papers[13-35] reporting diagnostic uses of AI in HPB surgery. Of these, five focused on the gallbladder, 11 on the liver, and seven on the pancreas. Twenty-nine studies reported prognostication[36-64] using AI, of which three focused on the gallbladder, 16 on the liver, one on the liver and pancreas, and nine on the pancreas alone. Almost half of the studies identified reported on the interventional use of AI[65-110] in HPB surgery (n = 46), with 24 studies focusing on the liver, 19 on the gallbladder alone or in conjunction with another organ (n = 4), and three studies looking at the pancreas. A summary of the papers subdivided into the diagnostic, prognostic and intervention cohorts can be found in Tables 1, 2, and 3, respectively.

Regarding sample size, most studies (n = 13) reporting diagnostic applications of AI in HPB surgery utilized data from fewer than 1,000 patients. The smallest number of patients in a focused study of the ultrasound-based classification of liver lesions was 22[14]. Three studies included over 5,000 patients and were included in our big data cohort[16,30,35]. The largest number of included patients was 199,783[30]. Most studies (n = 16) looking at prognostic uses of AI in HPB surgery had fewer than 500 patients. Two studies had fewer than 5,000 patients, but were included in our big data cohort due to the high number of images and image reports included[58,63]. Eleven studies looking at interventional uses of AI in HPB surgery did not use actual patient data, but used simulations-based approaches[69,70,75,76,81,82,84,85,91,92,104]. There was little mention or use of “explainable AI” concepts in any of the included studies.

Conceptual mapping of AI research in HPB surgery

Following data extraction and study classification, we undertook a conceptual mapping exercise to identify key areas and relationships in AI use [Figure 4]. Many of the identified concepts involved outcome prediction (such as the risk of complication, or personalized survival predictions). Others utilized AI to support clinicians in the identification of a condition before, during, or after surgery (such as identifying malignancy, identifying complications early, or even the prevention of these by using AI to alert clinicians to unseen structures intraoperatively). Preoperative planning and surgical simulation were particularly key areas within the intervention grouping. Finally, within the conceptual mapping exercise, we identified several areas where AI may be useful as either a risk stratification tool or as an intervention in future research (purple text, Figure 4).

Diagnostic applications of artificial intelligence

Diagnostic applications of AI primarily involved interpreting images using computer vision models [Table 1 and Figure 4]. AI was used across a range of imaging modalities, including transabdominal ultrasound, endoscopic ultrasound, MRI and CT, to identify lesions or classify lesions into different radiomic subgroups of disease. Although the majority of preoperative, diagnostic AI work focused on imaging, there were studies investigating perioperative risk prediction. However, there were no studies that proposed to use AI as an intervention in preoperative care pathways. Therefore, it should be considered that preoperative AI may also be undertaken with a broader surgical focus, rather than specifically targeted at HPB populations and hence are not discussed in this review.

Prognostic applications of artificial intelligence

The majority of prognostic applications for AI were in the prediction of cancer recurrence and survival [Table 2 and Figure 4]. This was achieved using a variety of input data, including imaging, genetics, and clinical characteristics. Prediction models were developed for a variety of time points, including the first 30 days following surgery and for longer-term survival.

Table 1. Summary of included studies focusing on diagnostic uses of AI in HPB surgery

Authors	Year of publication	Location	Organ	AI method	Aim	Method	Data
Saftoiu *et al.*[13]	2012	Romania	P	DL/CV	Assessed accuracy of real-time EUS elastography in pancreatic lesions using artificial neural network analysis	Prospective, blinded, multicentric study	EUS images
Kaizhi *et al.*[14]	2014	Japan	L	DL/CV	Proposes automatic classification method based on deep learning in contrast-enhanced ultrasonography (CEUS) of focal liver lesions	Case series	CEUS images
Gatos *et al.*[15]	2015	Greece	L	ML/CV	Design and implementation of a computer-based image analysis system employing the support vector machine system for the classification of liver lesions	Retrospective study	MRI images
Roch *et al*[16]	2015	USA	P	NLP	Implement an automated Natural Language Processing based pancreatic cyst identification system	Single institution prospective pilot study	Patient records
Sada *et al.*[17]	2016	USA	L	NLP	Evaluated whether natural language processing document classification improves HCC identification	Retrospective study	Pathology/radiology reports
Kondo *et al.*[18]	2017	Japan	L	ML/CV	Proposes automatic classification method based on machine learning in CEUS of focal liver lesions	Single institution pilot study	CEUS images
Yang *et al.*[19]	2017	China	L	NLP	Assess gene expression in HCC using combined data from The Cancer Genome Atlas and NLP identified genes	Description of experiment	Gene library/ published literature
Kuwahara *et al.*[20]	2019	Japan	P	DL	Investigate whether a deep learning algorithm using EUS images of IPMN could predict the diagnosis of malignancy	Retrospective study	EUS images
Shen *et al.*[21]	2019	China	P	ML	Establish and validate a radiomics diagnosis model for the classification of three subtypes of pancreatic lesion	Retrospective study	CT images
Lei Xu *et al.*[22]	2019	China/ USA	G	ML/CV	Develop and validate a prediction model for preoperative LN status evaluation in ICC patients	Retrospective study	MRI images
Brown *et al.*[23]	2019	Canada	L	NLP/ML	Explore natural language processing to predict downstream radiology resource utilization in patients undergoing surveillance for HCC	Retrospective study	Radiology reports
Watson *et al.*[24]	2020	USA	P	DL	Use CT-guided deep learning techniques to predict malignancy of PCNs	Retrospective pilot study	CT images
Liu *et al.*[25]	2020	China	L	NLP/DL	Designed an NLP pipeline for the direct extraction of clinically relevant features of liver cancer from radiology reports	Retrospective study	Radiology reports
Mao *et al.*[26]	2021	China	L	ML	Investigate the performance of an ultrasound-based radiomics approach to differentiate primary liver cancer from metastatic liver cancer	Retrospective study	US images
Jang *et al.*[27]	2021	South Korea	G	DL/CV	Evaluate the diagnostic performance of AI in differentiating biliary lesions using EUS images	Retrospective study	EUS images
Dongyan *et al.*[28]	2021	China	G	DL/CV	Assessed duodenoscopy assisted	Pilot study	ERCP/

					by visual sensing technology based on convolutional neural network algorithm in the diagnosis and treatment of gallstones		surgery images
Kim *et al.*[29]	2021	South Korea	G	DL/CV	Aimed to differentiate gallbladder polyps in ultrasound images using deep learning	Retrospective study	US images
Yamashita *et al.*[30]	2021	USA	P	NLP	Identify patients with pancreatic cystic lesions and extract measurements from imaging reports using NLP	Retrospective study	Radiology reports
Chong *et al.*[31]	2022	China	L	CV/ML	Investigate the impact of MRI-based radiomics on predicting GPC3 expression and the relevant recurrence-free survival in liver cancer	Retrospective study	MRI images
Liu *et al.*[32]	2022	USA	L	ML	Machine learning-based methods to select clinical and morphologic features to differentiate hepatocellular adenoma subtypes	Retrospective study	Pathology specimens/patient records
Schuessler *et al.*[33]	2022	Germany	L	ML	Differentiation of hemodynamically significant and non-significant coronary stenoses in patients undergoing evaluation for liver transplant	Retrospective study	CTA images
Chang *et al.*[34]	2022	China	G	DL	Explore the application value of the neural network and genetic algorithms in the detection and prognosis of tumor markers in patients with gallbladder cancer	Retrospective study	Tumor-markers
Kooragayala *et al.*[35]	2022	USA	P	NLP	Utilized an NLP algorithm to quantify the incidence of clinically relevant pancreatic lesions in CT imaging	Retrospective study	Radiology reports

CV: Computer vision; CTA: CT angiogram; CEUS: Contrast-enhanced ultrasonography; DL: deep learning; EUS: endoscopic ultrasound; GPC3: Glypican 3 (protein-coding gene); G: gallbladder; HCC: hepatocellular carcinoma; IPMN: Intraductal papillary mucinous neoplasm of the pancreas; ICC: intrahepatic cholangiocarcinoma; L: liver; ML: machine learning; LN: lymph node; NLP: natural language processing; PCN: pancreatic cystic neoplasms; P: pancreas.

Interventional applications of artificial intelligence

We identified several key concepts around supporting interventions with AI assistance [Table 3 and Figure 4]. Intraoperative vision was a major area, with multiple studies focusing on improving the visualization of unseen structures, which may cause significant patient harm if inadvertently injured (e.g., major blood vessels or the bile duct). This was achieved through virtual or augmented reality, where inputs from other data sources such as CT and MRI are combined (sensor fusion) and overlain on real-time images (e.g., through laparoscopic/robot-assisted surgery video source) to produce an augmented view of the surgical field.

Preoperative surgical planning and simulation were also identified as key concepts. There were numerous studies that aimed to develop virtual reality models or other digital interventions which permitted surgeons to plan complex operations with the aim of minimizing complications. This was proposed to be achieved through pre-surgery operative simulation/rehearsal (advantages when unusual anatomy identified) or by using AI methods to predict severe complications such as post-hepatectomy liver failure (PHLF).

Artificial intelligence tasks

We identified several common AI tasks being applied in HPB surgery. Classification is where data can be assigned to groups based on a defined shared characteristic. Classification algorithms were frequently

Table 2. Summary of included studies focusing on prognostic uses of AI in HPB surgery

Authors	Year of publication	Location	Organ	AI method	Aim	Design	Data
Singal *et al.*[36]	2013	USA	L	ML	Develop and compare predictive models for HCC development among cirrhotic patients using conventional regression analysis and machine-learning algorithms	Prospective study	Patient factors
Banerjee *et al.*[37]	2015	USA	L	ML/CV	RVI was assessed for its ability to predict MVI and outcomes in patients with HCC who underwent surgical resection or liver transplant	Prospective evaluation of a retrospective cohort	CT images
Walczak *et al.*[38]	2017	USA	P	ML	Assess the accuracy of artificial neural networks in predicting survival in patients with pancreatic cancer using both clinical and patient-centered data	Retrospective study	Patient factors
Ying Zhou *et al.*[39]	2017	China	L	ML/CV	Develop a CT-based radiomics signature and assess its ability to preoperatively predict the early recurrence (≤ 1 year) of hepatocellular carcinoma (HCC)	Retrospective study	CT images
Zheng *et al.*[40]	2018	China	L	ML/CV	Developed a CT–based radiomic nomogram to predict recurrence-free survival rates for HCC after resection, ablation, and transplant	Retrospective study	CT images
Ivanics *et al.*[41]	2019	Canada	L	ML	Leverage machine learning to develop an accurate post-transplantation HCC recurrence prediction calculator	Retrospective study	Patient factors
Sala Elarre *et al.*[42]	2019	Spain	P	ML	Evaluated the 2-year relapse risk for pancreatic cancer patients based on a machine-learning algorithm	Retrospective study	Patient factors
Marinelli *et al.*[43]	2019	USA	L	NLP/DL	Determine if weakly supervised learning/active transfer learning can hasten clinical deployment of deep learning models for liver segmentation	Retrospective study	Radiology reports/CT images
Naseif *et al.*[44]	2019	USA	P	ML/CV	Develop a delta-radiomic process based on machine learning to predict the treatment response of pancreatic cancer	Retrospective study	CT images
Shan *et al.*[45]	2019	China	L	ML/CV	A Prediction model based on peritumoral radiomics signatures from CT - investigate its efficiency in predicting early recurrence of HCC after curative treatment	Retrospective study	CT images
Chen *et al.*[46]	2020	China	L	CV/ML	Establish a radiomics-based clinical model for preoperative prediction of PHLF in HCC	Retrospective study	MRI images
Han *et al.*[47]	2020	South Korea	P	ML	Risk prediction model for POPF using AI	Retrospective study	Patient factors
Kambakamba *et al.*[48]	2020	Switzerland	P	ML	The potential of machine learning-based approaches to describe the pancreatic texture and to predict POPF	Retrospective study	CT images
Merath *et al.*[49]	2020	USA	L/P	ML	Assess ML algorithm to predict the patient risk of developing complications following liver, pancreatic or colorectal surgery	Retrospective study	Patient factors
Saillard *et al.*[50]	2020	France	L	DL	Evaluate the effectiveness of AI algorithms to predict survival following HCC resection	Development and testing of AI models	Histology images
Cesaretti *et al.*[51]	2020	France	L	ML/DL/CV	Automatizing liver-graft	Prospective	Surgery images

		Italy			segmentation from smartphone images and validating the robustness of this approach	study	
Mai *et al.*[52]	2020	China	L	DL	Establish and validate an artificial neural network model to predict severe post-hepatectomy liver failure in patients with hepatocellular carcinoma who underwent hemi-hepatectomy	Retrospective study	Patient factors
Liu *et al.*[53]	2020	Taiwan	L	ML	Devise a predictive model to predict postoperative survival within 30 days based on the patient's preoperative physiological measurement values	Retrospective study	Patient factors
Schoenberg *et al.*[54]	2020	Germany	L	ML	Developing and validating a machine-learning algorithm to predict which patients are sufficiently treated by LR	Retrospective study	Patient factors
Szpakowski *et al.*[55]	2020	USA	G	NLP	Determine the growth pattern of GPs and their association with GBC	Retrospective study	Radiology reports
Capretti *et al.*[56]	2021	Italy Portugal	P	CV/ML	Develop a reliable and reproducible machine learning-based multimodal risk model capable of predicting CR-POPF by combining radiomic features and morphologic features	Retrospective study	CT images/patient factors
Sun *et al.*[57]	2021	China	L	DL	Develop a model to predict HCC recurrence	Retrospective study	Patient factors
Xie *et al.*[58]	2021	USA	P	NLP	Develop and apply a natural language processing algorithm for the characterization of patients diagnosed with chronic pancreatitis	Retrospective study	Radiology reports
Hayashi *et al.*[59]	2022	Japan	P	ML	Predict recurrence and metastatic sites in pancreatic cancer following curative surgery	Retrospective study	Histology images
Li *et al.*[60]	2022	China	P	ML	Develop and validate clinical-radiomics models that preoperatively predict 1 and 2-year recurrence of PDAC	Retrospective study	CT images/patient factors
Noh *et al.*[61]	2022	South Korea	L	ML	Machine learning-based survival rate prediction of hepatocellular carcinoma patients	Retrospective study	Patient factors
Morris-Stiff *et al.*[62]	2022	USA	G	NLP	Develop a clinical prediction model for asymptomatic gallstones	Retrospective study	Radiology reports
Narayan *et al.*[63]	2022	USA	L	ML/CV	Developed an objective, computer vision artificial intelligence (CVAI) platform to score donor liver steatosis and compared its capability for predicting EAD against pathologist steatosis scores	Retrospective study	Histology images
Cotter *et al.*[64]	2022	USA	G	ML	Machine-based learning approach to stratify patients with gallbladder cancer into distinct prognostic groups using preoperative variables	Retrospective study	Patient factors

CV: Computer vision; CR-POPF: clinically relevant postoperative pancreatic fistula; EAD: early allograft dysfunction; G: gallbladder; GPs: gallbladder polyps; GBC: gallbladder cancer; L: liver; LR: liver resection; ML: machine learning; MVI: microvascular invasion; P: pancreas; PHLF: post-hepatectomy liver failure; POPF: postoperative pancreatic fistula; PDAC: pancreatic ductal adenocarcinoma; RVI: radiogenomic venous invasion.

Table 3. Summary of included studies focusing on interventional uses of AI in HPB surgery

Author	Year of publication	Location	Organ	AI method	Aim	Design	Data
Spinczyk *et al.*[65]	2012	Poland	L	ML	Measurement of liver motion during surgery	Single center feasibility study	Surgery videos
Okamato *et al.*[66]	2012	Japan	L/G	CV	Evaluate the utility of an image display system for augmented reality in hepatobiliary surgery under laparotomy	Case series	CT images
Fang *et al.*[67]	2013	China	L	CV	Assess the use of 3d planning for hepatectomy for hepatolithiasis	Retrospective study	CT images
Zein *et al.*[68]	2013	USA	L	CV	Establish anatomical precision and volumetric accuracy in 3D-printed models for donors and recipients undergoing LDLT	Prospective paired case series	CT/MRI images
Shahin *et al.*[69]	2014	Germany	L	ML	Develop a navigation approach to quickly compensate for tumor movements due to surgical manipulation	Description of experiment	US images
Yang *et al.*[70]	2014	South Korea	L	ML	Develop a user-centered 3D virtual liver surgery planning system algorithm	Pilot study	CT images
Fang *et al.*[71]	2014	China	P	CV	Investigate the clinical significance of 3-dimensional reconstruction of peripancreatic vessels for patients with suspected pancreatic cancer	Randomized parallel single-blind study	CT images
Begin *et al.*[72]	2014	Canada	L	CV	Evaluate an alternative automatic technique of liver volumetry based on a novel 3D virtual planning software and compare it to the manual technique	Prospective study	CT images
Bliznakova *et al.*[73]	2015	Bulgaria	L	CV/ML	Develop and test a software application for evaluation of the residual function of the liver prior to the intervention of the surgeons	Case series	CT images
Katic *et al.*[74]	2015	Germany	P/G	DL	Demonstrate the usefulness of deep learning model to identify surgical steps during laparoscopic cholecystectomy and pancreatic resections	Case series	Surgery videos
Song *et al.*[75]	2015	UK	L	ML	Describe a freehand laparoscopic ultrasound-based system that registers liver vessels in ultrasound with MR/CT data	Description of experiment and case series	US/CT/MRI images
Wang *et al.*[76]	2015	China USA	L	ML	Demonstrate the potential of homotopy-based SSC for shape-prior modeling in the liver surgical planning system	Description of experiment	CT images
Fang *et al.*[77]	2015	China	L	CV	Compare outcomes of surgery on centrally located HCC with and without 3D planning	Retrospective study	CT/MRI images
Zhang *et al.*[78]	2015	China	G	CV	Assess the use of 3d planning in surgery on bile duct cancer	Case series	CT images
Okuda *et al.*[79]	2015	Japan	G	CV	Evaluate the impact of 3D CT cholangiography on operative planning and outcomes of biliary malignancies	Retrospective study	CT images
Okamato *et al.*[80]	2015	Japan	P	CV	Evaluate the utility of navigation surgery using augmented reality technology for pancreatectomy	Case series	CT images
Fortmeier *et al.*[81]	2016	Germany	G/L	CV	Creation of a visuo-haptic simulation framework for the training and planning of the first steps of PTCD	Description of experiment	X-ray/US/CT images

Fusaglia *et al.*[82]	2016	Switzerland	L	CV	Present a novel LRS-based IGS system for laparoscopic liver procedures	Description of experiment	Laparoscopic surgery images
Ntourakis *et al.*[83]	2016	France	L	CV	Investigate the potential of AR-based navigation to help locate and resect colorectal liver metastases	Prospective pilot study	CT/MRI images
Mastmeyer *et al.*[84]	2017	Germany	L	ML	Compare axial force errors of simulated needle insertion for liver biopsy	Description of experiment	US/CT images
Sauer *et al.*[85]	2017	Germany	L	CV	Evaluates the application of a mixed reality head-mounted display for the visualization of anatomical structures during liver surgery	Case study	CT images
Cai *et al.*[86]	2017	China	L	CV	Report experience of using a 3d visualization system during hepatic resection	Case series	CT images
Miyamoto *et al.*[87]	2017	Japan	P	CV	3d planning - compared the pancreatic duct diameter and location with the intraoperative findings	Retrospective study	CT images
Hu *et al.*[88]	2018	China	L	CV	Assess the use of 3d planning for specific hepatectomy	Retrospective study	CT images
Mise *et al.*[89]	2018	Japan	L	CV	Assess how virtual hepatectomy conducted using surgical planning software influences the outcomes of liver surgery	Retrospective study	CT images
Mascagani *et al.*[90]	2019	Italy France	G	DL	Develop and test a method for consistent critical view of safety evaluation and reporting in videos which could be developed into the deep learning model	Pilot study	Laparoscopic surgery images
Teatini *et al.*[91]	2019	Norway	L	ML	Test if intraoperative imaging is necessary for accurate surgical navigation for laparoscopic liver resection	Description of experiment	CT images
Ho *et al.*[92]	2020	New Zealand	L	CV	Describe the computational pipeline that integrates into silico liver models and algorithms to aid surgical planning for liver resection	Description of experiment	CT/US/MRI images
Prevost *et al.*[93]	2020	Switzerland	L	CV	Evaluate the technical feasibility and the clinical impact of a new augmented reality system for laparoscopic liver surgery	Pilot study	CT/MRI images
Sandal *et al.*[94]	2021	Turkey	G	ML	Determine the usefulness of fuzzy logic algorithm to evaluate risk in patients undergoing laparoscopic cholecystectomy	Case series	Patient factors
Cervantes-Sanchez *et al.*[95]	2021	Mexico Germany	L/G	ML/DL	Machine/deep learning methods are combined with HSI-goal is the automatic discrimination using HSI of the bile duct from the gallbladder and liver	Description of experiment and case series	Hyperspectral images
Tokuyasu *et al.*[96]	2021	Japan	G	DL/CV	Develop a system that outlines laparoscopic cholecystectomy landmarks on endoscopic images in real time	Description of experiment and case report	Laparoscopic surgery images
Guzman-Garcia *et al.*[97]	2021	Spain	G	NLP/DL	Assess if analysis of surgeons' speech using natural language processing provide deeper insight into the surgical decision-making processes during laparoscopic cholecystectomy	Description of experiment	Audio transcripts of surgical videos
Imler *et al.*[98]	2021	USA	G	NLP/ML	Demonstrate the feasibility of using NLP to measure adherence	Retrospective study	ERCP procedure reports

					to ERCP quality indicators across individual providers		
Ruzzenente *et al.*[99]	2022	Italy	L	ML	Evaluate four difficulty scoring systems in liver surgery and determine the most important characteristics using random forest models	Case series	Patient factors
Mascagani *et al.*[100]	2022	France Italy	G	DL/CV	Creation of an assessment tool for CVS	Multicentre retrospective validation	Annotated surgery videos
Mascagani *et al.*[101]	2022	France Italy	G	DL/CV	Develop a deep learning model to automatically segment hepatocystic anatomy and assess the criteria defining the critical view of safety (CVS)	Case series	Annotated surgery images
Tranter-Entwistle *et al.*[102]	2022	New Zealand Australia	G	ML/CV	Use a commercially available ML-driven platform to evaluate a subjective grading of operative difficulty in laparoscopic cholecystectomy	Case series	Surgery videos
Liu *et al.*[103]	2022	China	G	ML/CV	Develop model and preliminarily verify its potential surgical guidance ability by comparing its performance with surgeons during laparoscopic cholecystectomy	Pilot study	Annotated surgery images
Ugail *et al.*[104]	2022	UK	L	ML/DL/CV	Present the use of deep learning for the non-invasive evaluation of donor liver organs	Pilot study	Surgical images
Mojtahed *et al.*[105]	2022	USA Netherlands Portugal	L	DL/CV	Demonstrate the accuracy and precision of liver segment volume measurements	Retrospective study	MRI images
Han *et al.*[106]	2022	China	L	DL/CV	Develop and validate a three-dimensional convolutional neural network model for automatic liver segment segmentation	Retrospective study	MRI images
Ward *et al.*[107]	2022	USA	G	DL/CV	Trained model to identify PGS	Development and testing of AI models	Annotated surgery images
Madani *et al.*[108]	2022	Canada USA UK	G	DL/CV	Develop and evaluate the performance of models that can identify safe and dangerous zones of dissection during laparoscopic cholecystectomy	Development and testing of AI models	Annotated surgery images
Loukas *et al.*[109]	2022	Greece	G	DL/CV	Framework for vascularity classification of the gallbladder wall from intraoperative images of laparoscopic cholecystectomy	Development and testing of AI models	Surgery images
Golany *et al.*[110]	2022	Israel	G	DL/CV	Developed algorithm and evaluated its performance in recognizing surgical phases of laparoscopic cholecystectomy	Development and testing of AI models	Annotated surgery videos

AR: Augmented reality; CVS: Critical view of safety; G: gallbladder; HSI: hyperspectral images; IGS: image guided surgery; L: liver; LDLT: living donor liver transplant; LC: laparoscopic cholecystectomy; LRS: laser range scanners; PTCD: percutaneous transhepatic biliary drain; PGS: parkland grading scale for cholecystitis; P: pancreas; SSC: sparse shape composition.

derived from imaging to group lesions into disease subgroups[15,18,21]. In another example, decision tree models were used to predict the occurrence of any complication and of specific complications in patients undergoing liver, pancreatic and colorectal surgery[49]. These algorithms were superior to the American Society of Anaesthesiologists (ASA) classification at predicting the chance of any complication. They performed well for specific complications, with c-statistics ranging from 0.76 to 0.98. As described in our conceptual mapping exercise, the augmentation of surgical fields to highlight relevant anatomy is a key area

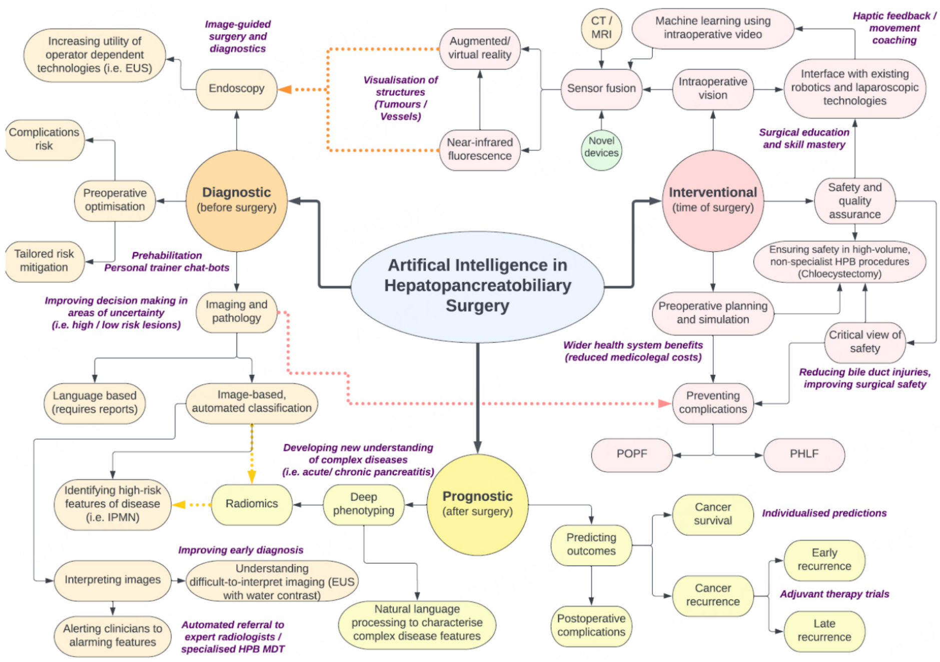

Figure 4. Conceptual mapping of areas of AI research in HPB surgery, stratified by treatment timing. This exercise identified several areas of overlap (dashed arrows) across different divisions, in addition to several areas where AI would be useful for future research (purple free text). CT: Computed tomography; IPMN: intraductal papillary mucinous neoplasm; MRI: magnetic resonance imaging; PHLF: post hepatectomy liver failure; POPF: postoperative pancreatic fistula.

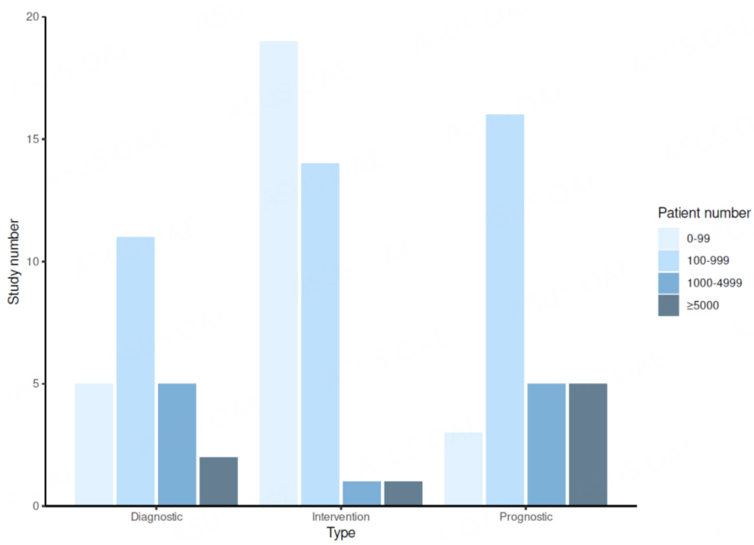

Figure 5. Number of studies utilizing large datasets stratified by AI approach.

of research. This is an example of object detection and is a task well suited to laparoscopic cholecystectomy. Madani *et al.* describe a deep learning algorithm that intraoperatively recognizes "go," or "no-go" areas of dissection to minimize the risk of adverse events such as bile duct injury[108].

The intersection of AI and big data in HPB surgery

We identified eleven studies utilizing large datasets in HPB surgery applications [Table 4]. Nine have been published since 2020. Eight of the 11 identified papers utilized NLP to extract data from large numbers of reports, mainly with the aim of identifying patients with a specific condition, either for phenotyping or to identify patient cohorts. The majority originated from the USA (n = 9; 82%), with one study from China and one from South Korea [Figure 5].

An example of the use of an NLP algorithm to identify patient cohorts and devise a means of following-up incidental scan results was by Kooragayala *et al.*[35]. This study used a keyword search associated with suspicious pancreatic lesions in over 18,000 patients who underwent a CT scan following trauma over a 10-year period. The approach identified pancreatic lesions in the reports of 232 patients, of which 48 were intraductal papillary mucinous neoplasms (IPMNs). In addition, this paper proposed a management flowchart for incidentally found pancreatic lesions. A further example of the use of NLP in high-volume data was demonstrated by Morris-Stiff *et al.*[62], who used NLP to identify asymptomatic gallstones from a cohort of 49,414 patients. They were then able to identify risk factors for progression to symptomatic gallstone disease in this asymptomatic cohort and showed an approximately 2% risk of symptomatic progression per year.

DISCUSSION

This review has identified a rapid increase in the quantity of AI research conducted within HPB surgery. Much of this is focused on intraoperative applications of AI, such as the use of image analysis and computer vision to address diagnostic and prognostic uncertainties. In addition, the use of 3D reconstruction and augmented reality models coupled with data-driven prediction algorithms has emerged as an important area, particularly in preoperative planning and intraoperative decision-making in liver surgery. Artificial intelligence methods have the most to offer in the distillation of multi-dimensional information to tractable knowledge that can be applied to individual treatment decisions. HPB surgery represents a good target for these technologies, given the frequently complex disease patterns and diverse treatment pathways employed.

Most artificial intelligence approaches rely on large volumes of data for training purposes. Of the commonly described features of big data, the included studies reflect “volume” and “variety” with fewer utilizing real-time rapidly changing data (“velocity”). Data sources included large pre-existing databases, collated images and imaging reports. Two notable databases used were the Cancer Genome Atlas and the American College of Surgeons National Surgical Quality Improvement Program (NSQIP) database, which were widely used across a range of studies. Natural language processing was frequently employed to extract information from imaging reports and other healthcare text sources. In one study, NLP was used to identify concerning pancreatic lesions in historical imaging reports[35]. This demonstrates the depth and flexibility in AI techniques to adapt to changes in patient management over time - the malignant potential of particular pancreatic cysts has only been appreciated in recent years. Moreover, these approaches may be adapted to help non-specialists managing HPB conditions, particularly in low-resource settings with limited access to tertiary HPB services. As computer vision approaches improve, the supplementation of local imaging and pathology reporting with AI-derived diagnostic support may leapfrog the requirement for massive and often unaffordable training of humans to perform these tasks.

There are, however, genuine risks of bias arising with the development of these techniques. We found significant geographical variation in current research, with no studies incorporating data from low- and middle-income countries (LMICs). If the benefits of AI are to be shared equitably across contexts, then investigators must consider how solutions can broadly generalize between populations and avoid

Table 4. Summary of studies leveraging large datasets for AI use in HPB surgery

Author	Year of publication	Study description
Roch *et al.*[16]	2015	566,233 CT reports from 50,669 patients analysed for keywords associated with Pancreatic Cysts using NLP
Yang *et al.*[19]	2017	The Cancer Genome Atlas catalogs genes associated with 33 cancers. Genes associated with HCC were extracted from database and checked for overlap with genes identified in 35 years of published literature using NLP
Merath *et al.*[49]	2020	15,657 patients undergoing liver, pancreatic or colorectal surgery (685 liver and 6,012 pancreatic) retrospectively were identified from the American College of Surgeons National Surgical Quality Improvement Program database. Risk-prediction Machine Learning model created from pre-op characteristics
Szpakowski *et al.*[55]	2020	365 Gallbladder Cancer and 35,970 Gallbladder Polyp patients were identified from 622,227 patients in a Californian health system. NLP was used to identify Polyps from Ultrasound reports
Xie *et al.*[58]	2021	58,085 imaging reports from 6,346 Chronic Pancreatitis patients were used to develop an NLP algorithm that could characterize features of Chronic Pancreatitis
Yamashita *et al.*[30]	2021	430,426 imaging reports from 199,783 patients were used to create an NLP algorithm to identify the presence and size of Pancreatic Cysts
Imler *et al.*[98]	2021	23,674 ERCP reports were analyzed for quality measures using NLP
Noh *et al.*[61]	2022	Machine learning-based prediction models for survival applied to 10,742 HCC patients
Morris-Stiff *et al.*[62]	2022	Ultrasound reports identified 49,414 patients with gallstones. NLP algorithm trained to identify asymptomatic patients (22,257)
Narayan *et al.*[63]	2022	25,494 images from 90 liver biopsies were used to develop Machine Learning Computer Vision models to score liver steatosis
Kooragayala *et al.*[35]	2022	NLP was used to identify pancreatic lesions from 18,769 adult trauma CT reports

CT: Computed tomography; ERCP: endoscopic retrograde cholangiopancreatography; HCC: hepatocellular carcinoma; NLP: natural language processing.

exacerbating pre-existing healthcare disparities. This is a widely discussed and controversial topic in the broader AI field. Inherent systematic biases in datasets clearly exist, with some of the most obvious reflecting racial, socioeconomic and gender-based prejudices. Addressing these complex issues is crucial across all AI work, including in HPB surgery. The majority of HPB disease occurs LMICs[111], so it is essential that these populations are better represented in current HPB research more broadly and AI research specifically.

In addition to geographical disparities, concerns around the transparency of AI algorithms and lack of explainability are likely to hamper uptake and trust in clinical practice[112]. The need for explainability is rooted in evidence-based medicine, which relies on transparency and reproducibility in decision-making[113]. Without explainable AI, patient trust in healthcare will erode. Others have argued that true explainability represents a false hope, and that explainability methods cannot deliver meaningful patient-level interpretability[114]. The focus should be on robust internal and external validation. In this review, we found little reference to concepts of explainability in included studies. It is important that these issues are explored and addressed, particularly when developing algorithms orientated toward patient-facing prognostication. As AI systems transition from research to clinical practice, transparency and reliability are paramount if trust is to be built and maintained[115,116].

The ability to understand and reproduce scientific findings is imperative, yet reporting the quality of included studies was variable. A number of useful reporting guidelines now exist, specifically orientated toward AI. In 2019, a rigorous process of literature review, expert consultation, Delphi survey, and consensus meeting resulted in the SPIRIT-AI (Standard Protocol Items: Recommendations for Interventional Trials - Artificial Intelligence) and CONSORT-AI (Consolidated Standards of Reporting Trials - Artificial Intelligence) standards[117]. In addition, two additional tools are currently under development: Transparent Reporting of a multivariable prediction model of Individual Prognosis Or Diagnosis AI extension (TRIPOD-AI) and the Prediction model Risk Of Bias Assessment Tool (PROBAST-AI)[118]. These promise to provide standardization and assessment tools that will greatly increase the quality of clinically-orientated AI study reporting.

Where should AI research in HPB be focussed? Most studies in this review concentrated on image analysis. While this is an important area, there are many other challenges in HPB which could benefit from the application of AI. Research prioritization in AI must be determined by broad stakeholder groups, led primarily by the patient and public representatives, accounting for a range of viewpoints and actively engaging non-technical individuals in the design and delivery of research studies. We found little mention of engagement with stakeholder groups in included studies (e.g., patients, clinicians and the wider HPB community), which is crucial if these complex interventions are to move into clinical practice successfully. Moreover, included studies focused on the development of AI models rather than on the implementation of AI systems. While this is understandable given the current stage of development, future work should focus on how broader AI-driven systems can be implemented safely into clinical pathways and be clear about the function they serve.

Our study has several limitations. First, there is significant heterogeneity in the content and outcomes of the various studies included. While meaningful comparisons are challenging, a useful overview of common issues and themes affecting AI research in HPB is provided. Second, as is the nature of a scoping review, it is possible that studies meeting the inclusion criteria have been omitted, leading to an incomplete presentation of the current literature. For example, papers focusing on NLP and the gallbladder were relatively poorly represented in exploratory literature searches, possibly reflecting poor search descriptors and study labeling. Finally, as AI and associated concepts are undergoing rapid development, study inclusion criteria are in flux. Improving formal definitions in these emerging fields will help study classification and ease of literature identification.

The use of AI and big data in HPB surgery and medicine, more generally, is rapidly expanding. AI promises benefits in the delivery of clinical care and may result in future improvement of healthcare outcomes. This review identifies crucial interlinking conceptual areas of AI as applied to HPB surgery. Future research must address issues of bias, transparency, and explainability and ensure that innovation is representative of HPB patient populations across the world.

DECLARATIONS

Authors' contributions

Participated in the design of the study, data collection, screening, interpretation and presentation, writing of the manuscript and submitted the manuscript: McGivern KG

Participated in the design of the study, data collection, screening, interpretation and presentation, and critical evaluation of the manuscript: Knight SR

Participated in the writing and critical evaluation of the manuscript: Drake TM

Participated in data screening and presentation: Lucocq J

Participated in the critical evaluation of the manuscript: Bernabeu MO, Clark N, Fairfield C, Pius R, Shaw C, Seth S

Participated in the design of the study and critical evaluation of the manuscript: Harrison EM

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