From data interoperability to ‘moral interoperability’ in the global health data architecture: integrated use case of AI-driven computational ethical analysis with Bayesian-propensity score and cost-benefit analyses optimizing efficiency and equity in colorectal cancer

De la interoperabilidad de datos a la “interoperabilidad moral” en la arquitectura mundial de datos sanitarios: caso de uso integrado de análisis ético computacional impulsado por IA con puntuación de propensión bayesiana y análisis de costos y beneficios que optimizan la eficiencia y la equidad en el cáncer colorrectal

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Abstract

The surging health and financial costs of diseases, disabilities, and disparities support the global acceleration of interests and investments in health AI for better, cheaper, faster, and fairer health solutions globally and locally. Yet there is no consensus on practically operationalizing responsible AI principles across diverse global sectors, states, and belief systems. This proof-of-concept study utilizes the global pluralistic ethical framework (the Personalist Social Contract) to therefore provide the first known Bayesian augmented AI-driven Computational Ethical (AiCE) and policy analysis integrating clinical, cost effectiveness, and healthcare disparity analyses with nationally representative data to estimate the global cost of healthcare disparities in colonoscopy (CS) and the savings from AI-enabled CS to reduce them. It suggests that reversing racial disparities particularly for Hispanics and Asians may save American healthcare systems $17.61 billion annually, with AI-augmented CS potentially contributing savings of $625.40 million for Hispanics and $289.00 million for Asians in particular (with similar cost savings for vulnerable communities in middle and low-income countries also). The above findings support the cost savings imperative for such strategic and capacity-building investment in these AI-driven measures to improve healthcare's strategic aims of Sustainability, Effectiveness, Efficiency, and Equity (SEEE). Such empirical results inform the larger global bioethical argument from the twin dimensions of human dignity and human security (rooted in the personalist, multicultural, and metaphysical account of the person as a member of the global human family) to highlight the AI ethical imperative to optimize the performance of the global digital health ecosystem. Such an instrumental end is a critical means of advancing toward the ultimate end of the common good, in which the individual good of each person is safeguarded and in which it finds her/his fulfillment working toward.

Keywords: colonoscopy, cost effectiveness, disparities, AI, moral interoperability.

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1. Introduction

There is widespread multi-sector consensus internationally sharpened by the COVID-19 pandemic that modern healthcare fails to consistently and equitably deliver quality, safe, affordable, and accessible care (1). Patients on average may receive only half of the standard of evidence-based care, up to 75% of diagnoses may be inaccurate (especially in low-and middle-income countries), medical error may be as high as the third leading medical cause of death, and despite a doubling of healthcare costs and explosive growth in disparities in the last 20 years, the quality and safety of care has not sustainably improved (2-5). A 2020 Harvard University analysis concluded that the pandemic most recently highlighted the "hollowness of the global health rhetoric of equity, the weaknesses of a health security-driven global health agenda, and the negative health impacts of power differentials not only globally, but also regionally and locally," and thus it strengthens the imperative for modern healthcare to "reimagine and repair the broken systems of global health" especially as healthcare requires globalized supply chains and collaboration from diverse partners (6). Accordingly, there is surging public-private interest for innovative and ethical artificial intelligence (AI)-driven digital transformation of healthcare systems that are efficient, transparent, safe, reliable, and fair (1,7). Understanding healthcare as a global healthcare ecosystem and plugging it in to the larger AI-driven Internet of Things-powered global digital ecosystem is already enabling surging successes internationally: integrating a myriad of actors (hospitals, clinics, clinicians, executives, businesses, technology firms, community organizations, and governments spanning diverse belief systems and nations) to leverage their complementary capacities for subsequent explosive force-multiplying technologies (linking data and capacities from smart phones, mobile and remote monitoring devices, electronic health records (EHRs), business dashboards, public data sources, social media, and cloud-based data architecture and computing) to deliver more accurate, affordable,

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rapid, adaptive, personalized, and equitable care (which is ultimately higher-value add at the individual and population levels) (1,8-10). Amid the 2022 dramatic escalation of geopolitical conflicts and economics strains undermining healthcare throughout the increasingly muti-polar world, there is nonetheless sustained confidence about the substantive net benefit for patients, providers, and payors across healthcare systems, belief systems, and nations to have health AI that protects individual human dignity, while advancing human security, societal stability, economic prosperity, and thus national security by optimizing populations' wellbeing, equity, and productivity (11).

Yet such progress is undermined by the paucity of effective, practical, and integrated healthcare AI methodologies creating, deploying, and iteratively optimizing such successful and ethical healthcare AI at scale. Technically effective AI is not necessarily the same thing as clinically relevant tools nor those that are cost effective or societally equitable to enable successful scale and sustainability. Therefore, AiCE or AI-driven Computational Ethics and policy analysis (AiCE) has been developed and deployed to integrate clinical, ethical, and cost effectiveness analyses for healthcare system optimization at the strategic, organizational, and clinical levels concurrently by seamless, embedded, and comprehensive integration in the clinical workflows and unique cultures of healthcare systems within their overarching organizational, data architecture, and political economic structures (1,12).

Yet there still remain few comprehensive proof-of-concept demonstrations for such an approach, let alone their practical feasibility and superior cost effectiveness to alternative or piecemeal approaches, further slowing the successful AI-driven transformation of value-based healthcare systems. Healthcare appears to increasingly need AI, and AI needs successful clinical and economic demonstrations for healthcare to adopt the technology in an ethical, responsible, and sustainable manner. To advance ethical AI, it seems that it also requires complementary clinical and economic demonstrations. Two recent systematic reviews of cost effectiveness studies

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for healthcare AI demonstrate that across 5,704 candidate studies to date, the vast majority are limited to the United States (US) and lacked sufficiently detailed methodologies to allow replication, high quality rating, focus on underserved and lower income communities (disproportionately poised to benefit from such technology), and end-to-end integration or at least feasibility for sustainable adoption by healthcare systems' existing workflows and structures (1,13-14). The landmark 2021 report by the World Health Organization (who) on global AI ethics provided a substantive step forward by providing six consensus principles on AI health ethics (15). And yet there are little to no publications or studies to date that deploy a global, comprehensive, integrated, concrete approach translating general principles into relevant, useable, defensible, and real-time guidance and augmentation for strategic, organizational, and clinical decision-making to prevent, mitigate, and solve AI ethical dilemmas (1,16). This absence unfortunately only undermines the reliably of AI algorithms (as the engineers designing them generally lack the ethical and clinical training for them to be defensible and relevant for healthcare) and their trustworthiness (as the hidden assumptions of such AI limits multi-disciplinary scrutiny, debate, and consensus-based decision-making in ways that respect the often competing and conflicting values, objectives, and priorities of the diverse actors that constitute the global healthcare ecosystem and their included healthcare systems).

Therefore, this paper produces a series of conceptual and practical novel developments for AI-transformed healthcare optimizing Sustainability, Effectiveness, Efficiency, and Equity (SEEE) as the defining criteria for this emerging model of the AI-powered future of health. Toward this goal, the paper is the first to demonstrate the following analytic advances: global computational ethical analysis of AI (focusing on the concrete use case in colorectal cancer (CRC)), AI-augmented analysis for such, comprehensive analysis integrated clinical with cost and ethical dimensions, global bioethics analysis drawing explicitly in diverse belief and ethical systems, analysis high-

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lighting disparity reduction emphasizing lower income countries and healthcare systems, and practice-focused application of these analytic results in the global digital healthcare system within which the world's healthcare systems operate. CRC was selected as the primary clinical domain given its international relevance and growing AI use cases in it, in addition to the clinical, economic, and public health impacts of CRC that is currently the third most common cancer globally, costs upwards of $190 billion globally, inflicts disproportionate burden based on region, and yet is generally preventable (through lower cost behavioral changes and early screening, which nonetheless is lacking particularly in lower income communities, and could be addressed by effective collaboration across partners in the global ecosystem sharing AI-augmented technical and clinical expertise and resources) (17).

2. Methods

2.1. Data source

The data source for this study is the largest publicly available US all-payer inpatient healthcare administrative dataset spanning approximately 4,500 hospitals in 50 states, the National Inpatient Sample (NIS), sponsored by the Agency for Healthcare Research and Quality (AHRQ) within the US Department of Health and Human Services (DHHS) (18). From 2016 onward, the NIS adopted the International Classification of Diseases, Tenth Revision, Clinical Modification (ICD-10-CM). The dataset includes demographic, comorbidity, procedural, complication, mortality, length of stay, total cost, and hospital characteristics for each hospitalization. The 2016, 2017, and 2018 NIS datasets were selected for this study as they are among the latest available datasets and the first to use ICD-10 coding and so better reflect current clinical trends in diagnoses, treatments, and outcomes compared to prior years. Study inclusion criteria included all NIS hospitalizations for adults aged 18 years or older

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during the above index time periods. Per the US DHHS and National Bureau of Economic Research, no review by an Institutional Review Board (IRB) is required for the NIS under the HIPPA Privacy Rule since the NIS is a limited data set (in which 16 direct identified specified by the Privacy Rule have been removed) (19-20). This study used de-identified data and was conducted according to the ethical principles in the Declaration of Helsinki.

2.2. Study design

To conduct a more comprehensive analysis more broadly and practically applicable within current healthcare systems, the primary analysis consisted of AiCE according to its first empirical (clinical then economic) step then the second ethical-policy step using the Personalist Social Contract (PSC) ethical framework. The first empirical step featured a nationally representative retrospective longitudinal multicenter cohort analysis of total cost among all hospitalized adults. It additionally utilized Machine Learning-augmented Propensity Score adjusted multivariable regression (ML-PSr) within BAyesian Machine learning-augmented Propensity Score translational (BAM-PS) statistics. A cost analysis was then conducted using the above clinical results. This empirical step was followed by the final ethical-policy step in which the above AI-augmented empirical results informed a pluralistic-based global bioethical analysis to optimize equitable care for the above patient populations.

2.3. Regression statistical analysis, machine learning analysis, and model optimization overview

The primary outcome was total hospitalization cost (in U.S. dollars ($)) and secondary outcome was inpatient mortality (yes/no). To maximize the likelihood of internally and externally valid and replicable results, a regression model performance was optimized according to the following sequential process. First, variables that were

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clinically or statistically significant were identified in the existing literature, clinical practice, and bivariable analysis to be considered in the final regression models. Second, those variables were included in the forward and backward stepwise regression to augment decision-making on the variables ultimately included in the final regression models; the propensity score for CS was created based on the below protocol additionally and included as an adjusted variable in the regression model. Third, the regression results were compared to those generated by backward propagation neural network ML to ensure comparability by root mean squared error and accuracy. Fourth, the regression model performance was additionally assessed with a correlation matrix, the area under the curve, Hosmer–Lemeshow goodness-of-fit test, Akaike and Schwarz Bayesian information criterion, variance inflation factor, and tolerance, multicollinearity, and specification error. Fifth, the models were iteratively run to fine-tune models until the above process confirmed optimal performance with the final models and included variables.

2.4. BAyesian Machine learning-augmented Propensity Score translational (BAM-PS) statistics

BAM-PS statistics were performed on the NIS to inform cost-benefit analysis. BAM-PS is a novel hybrid analytic methodology combining ML-PSr (for traditional statistical methodology with causal inference-based propensity score analysis, augmented by ML capable of handling higher dimensional, more complex, and faster data streams) with Bayesian analysis (with informative priors integrated with ML-PSr results) (21-23). BAM-PS seeks to preserve internal validity in analytic methodology while expanding it (i.e. by reducing the likelihood of relevant omitted variables) and external validity (by increasing generalizability through greater number of data sources to more accurately and precisely reflect real-world clinical practice in real-time for more timely, accurate, precise, and relevant predictions to augment organizational and clinical decision making in the

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AI-augmented and transforming healthcare systems). BAM-PS enables both direct (through integration) and indirect (through informative priors) linked datasets and data streams. The rational for the use of the NIS dataset and the ML-PSr underlying BAM-PS with it (with the rationale including its comparative advantages versus competing statistical, AI, statistical-AI hybrid, and other causal inference techniques) are documented in the above cited prior studies. Regression within ML-PSr was conducted for total hospitalization cost and mortality. The propensity score for the likelihood of undergoing CS was first created (utilizing the same above variables used in the final regression model given the double propensity score adjustment method), a balance was confirmed among blocks, and then the propensity score was included in the final regression models as an adjusted variable (24-25). Socio-demographic disparities for total hospitalization costs were thus assessed in the NIS with BAM-PS among US patients and then extrapolated to the global population, adjusting for the worldwide population distribution and country-averaged healthcare utilization and healthcare costs (generally with lower expenditures and hospitalization rate outside the US) (26-30).

2.5. Cost-benefit analysis

Cost-benefit analysis was conducted according to the widely used technique quoted by the US Centers for Disease Control and Prevention (CDC) as the monetary valuation of an intervention (AI-enabled CS) minus the costs of implementing the intervention in US dollars (31). The AI implementation costs were calculated as the average per CS costs of available AI on the US market (as of October 2020), with a 3% discount rate annually for future costs (32). The direct and indirect clinical costs were calculated using a societal perspective (spanning patients, families, employers, and healthcare systems) based on the peer-reviewed literature and 2018 Centers for Medicare & Medicaid Service reimbursement rates, including for the costs of screening CS (assuming 60% screening population uptake)

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and cancer treatments costs (including those required to address adverse events of the treatment) using current US screening and treatment guidelines. The benefit was calculated as the reduced total costs above with versus without AI augmented CS from reduced cancer incidence and mortality, by improving detection and early effective treatment of pre-cancerous and cancerous growths (utilizing an adenoma detection rate gradient of 28-40%). The first phase of the cost-benefit analysis utilized the results from a large 100,000 subject study in The Lancet that utilized the above inputs for screening CS in a Markov model microsimulation for US individuals 50-80 years of age at average risk of colorectal cancer, using both every 10-year screens and once-in-life screening CS. The above cited study was selected for cost-benefit analysis inputs given its large size, recency, and rigorous methodology, in addition to the high global health and financial burden of CRC (in screening, treatment, morbidity, and mortality at the individual and population level) and the general absence of such above high-quality studies on the cost effectiveness of healthcare AI (including the general absence of datasets for granular high-quality cancer and pre-cancer screening). The second phase of the cost-benefit analysis extrapolated the results internationally based on the global population distribution, healthcare utilization, and country-averaged healthcare costs to account for the differences between the US and the rest of the world (while seeking to minimize unnecessary number or complexity of assumptions to improve model validity and explainability).

2.6. AI-driven Computational Ethics and policy (AiCE) analysis

The second or ethical-policy step within AiCE was then conducted by integrating the above quantitative analyses with ethical analysis using the pluralistic global bioethical framework of the PSC (1,16,33). The PSC is a novel integration of modern ethics (principally utilitarianism-informed Rawlsian social contract of political liberalism, bounded by Kantian deontology and informed by feminist, Marxist,

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deconstructionist, and ecological ethics) and classical ethics (principally Thomistic-Aristotelian virtue ethics, articulated by William Carlo's esse/essence revision of Norris Clarke's Strong Thomistic Personalism, a derivative formulation of Thomism as a development of classical Aristotelianism metaphysics) (34-37). It uniquely articulates the philosophical foundation and framework of the United Nation's 1948 Universal Declaration of Human Rights (UDHR), founded on the primary metaphysical principle of human dignity and resultant rights and duties, which has since united the world's diverse belief systems and 193 nations in what has become the dominant modern ethical framework and foundation of international law. As such, the PSC entails an extended defense of a metaphysics of multiculturalism that explicitly cites and anchors itself in the world's diverse belief systems (including in their canonical texts as applicable) and elaborates the substantive converging (not simply Rawlsian-like overlapping) consensus as the metaphysical (not simply political) identity of the person individually, and thus the criteria for justice and its subsequent peace communally in the global community of persons sharing a common humanity. The PSC was additionally chosen as the primary ethical framework for historical reasons following the 2020 Rome Call for AI Ethics, which served as the first cross-sector global standard for AI ethics for practical application. Before signing the declaration, the co-signing parties (including Microsoft, IBM, the UN Food and Agriculture Organization, the EU's Italian Ministry of Innovation, and Vatican City (representing through its bioethical academy scholars from the world's diverse religions, affiliated and unaffiliated) first advanced its theoretical foundation by recognizing the PSC as part of the convention's award to the world's top doctoral dissertation on AI ethics. The Rome Call's consensus cited the UDHR to ground the enumerated principles of transparency, inclusion, accountability, impartiality, reliability, and secure privacy for responsible AI. The PSC details and defends the substantive metaphysical and ethical underlying these principles while also demonstrating their concrete applications. Echoing the

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Rome Principles, the ensuing European Union and US Department of Defense 2020 frameworks led up to the similar 2021 WHO report (with significant overlap in consensus principles for health AI) which built on this historical trajectory to generate more detail to this UDHR-informed principal framework to operationalize it in modern healthcare. Thus, the seminal Rome Principles (informing later global AI ethical standards) were explicitly rooted in the UDHR, and the PSC demonstrates philosophically and historically its Thomistic Aristotelian foundation and modern social contract framework. Practically, the PSC was additionally chosen as it is designed to operate within AiCE's embedded, augmented, automated, and iterative design within healthcare system operations (organizationally and clinically), has been utilized extensively to optimize healthcare efficiency and equities (including in population health, cardiac arrest, COVID-19 and related pandemics, bioterrorism, and modern armed conflicts), and provides a substantive articulation and defense of the moral interoperability foundation critical for an effective data interoperability framework and unifying strategic orientation of the diverse partners in the global digital health ecosystem to survive 21st century challenges and beyond.

2.7. Quality control, result reporting, and analytic software

An academic physician-data scientist, biostatistician, and ethicist (DJM) confirmed that the final analytic models were sufficiently supported by the existing literature and related theories. Fully adjusted regression results were reported with 95% confidence intervals (CIs) with statistical significance set at a 2-tailed p-value of <0.05. Statistical analysis was performed with STATA 17.0 MP edition (STATACorp, College Station, TX, USA), and ML analyses were performed with Java 9 (Oracle, Redwood Chores, CA, USA).

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3. Results

3.1. BAM-PS healthcare disparities and cost-benefit analyses

Of the 148,755,036 adult hospitalizations from 2016-2020, 788,402 (0.53%) underwent CS; Hispanics (9.83%) and Asians (2.71%) compared to Caucasians (69.39%) were significantly less likely to receive CS (all $p<0.001$) despite Hispanics, Asians, and Causians respectively accounting for 13.09%, 3.13%, and 63.61% of the total hospitalized adult sample as seen in Figure 1. In BAM-PS utilized in the NIS, there were significantly increased total hospitalization costs for the following: Hispanics ($12,948.12, 95%CI 9,455.89-16,440.35; $p<0.001$) and Asians ($12,338.22, 95%CI 5,959.84-18,716.60; $p<0.001$) versus Caucasians, in addition to the highest income quartile ($6,779.03, 95%CI 3,522.23-10,035.84, $p<0.001$) versus the lowest, independent of clinical severity, comorbidities, and NIS-calculated mortality risk by disease related group (there were no other such socio-demographic disparities including by insurance, urban density, or region, nor were there any significant inpatient mortality disparities based on the above variables). This translates to $244.30 million and $59.35 million extra in racial disparities annually in the US alone for Hispanics and Asians respectively undergoing CSs, independent of clinical confounders. Adjusting for global population distribution, healthcare utilization, and country-averaged healthcare costs, this translates into $16.96 billion and $648.20 million annual costs of racial disparities for Hispanic and Asian patients internationally every year undergoing CSs compared to their Caucasian peers. In cost-benefit analysis, CS with versus without AI globally produced $3.49 billion saved overall, including $625.40 million saved for Hispanics and $289.00 million saved for Asians.

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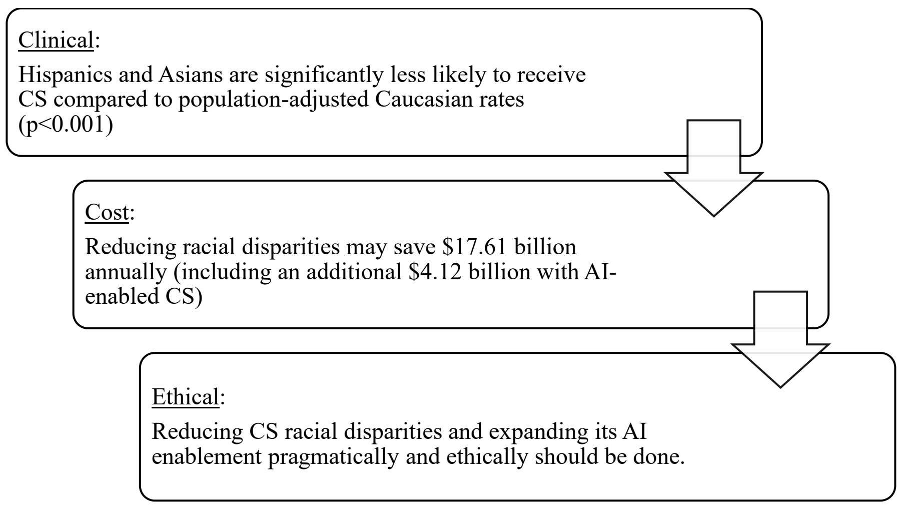
Figure 1. AiCE integrated analysis: Clinical, cost, and computational ethical results for equitable colonoscopy (CS) utilization from 2016-2020 in a nationally representative United States sample (N=788,402)



Source: prepared by authors.

3.2. AI-driven computational ethics and policy (AiCE) analysis: Personalist Social Contract

The above clinical and economic results then informed the final or focused ethical-policy analysis step of AiCE. The primary material object of this ethical analysis was healthcare cost, the primary context was colorectal cancer screening and management, and the primary formal object or ethical analytic framework is the PSC. Applied to this concrete ethical situation, the formal PSC argument is as follows:

> (Premise 1) CRC carries a high clinical, cost, and disparity burden globally that can be effectively and efficiently reduced by modifiable behavior changes and screening, the latter particularly enabling early intervention before cancer diagnosis and

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progression especially key for lower income countries and healthcare systems.

(Premise 2) There appear to be significant disparities among patients undergoing CSs by race and income that are not sufficiently explained by clinical severity, comorbidities, and other medical factors, particularly with Hispanic and Asian minorities having significantly increased hospitalization costs with CS compared to Caucasians.

(Premise 3) Life and equal societal protection are fundamental individual and state rights, logically derivative from the dignity of the human person, central to human and national security, and are politically enshrined across the United Nations, numerous international institutions, and the majority of nations' constitutions and legal statutes.

(Premise 4) Respect for dignity at the individual level requires respecting the person's rights to goods (beginning with the primary good of life) necessary for the person to develop through a just and stable commitment to the common good and thus the community in reciprocal care for the individual.

(Premise 5) Respect for dignity at the communal level requires respecting other cultures as the communal manifestations of their constitutive individuals seeking through justice the common good (as the objective good of the community, entailing the objective good of individual flourishing, subjectively experienced as the ultimate individual good of self-actualization through justice, completed in love, uniting the person to the community which is united and animated by goodness itself).

(Premise 6) Social disparities in CS outcomes including by race can produce disproportionate health and financial burdens on those social sub-communities, resulting in a disproportionate threat to the preservation of those persons and related cultures, and accelerating the impoverishment of the global human community with the loss or diminishment of those individuals and cultures; such disparities further undermine the political eco-

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nomic stability of those related national and global societies by reducing societal equity, cohesion, and productivity.

(Premise 7) The reversal of such disparities may result in $17.61 billion saved annually globally, which may be aided by the significant cost savings of AI-enabled CS (particularly for lower income countries and healthcare systems with fewer resources for CRC treatment).

(Premise 8) Continued disparities in effective management of CRC undermine respect for the rights of patients and their cultures (and their human and national security), which are critical to the wellbeing and stability of societies that encompass all peoples, cultures, and goods.

(Premise 9) Successful deployment, optimization, and scale up of this AI-augmentation of CS can successfully leverage this integrated justification only if sufficient moral interoperability underlying sufficient data interoperability is achieved in the global digital health ecosystem align, unite, and empower the ecosystem's diverse healthcare systems and their government, business, and community partners toward the shared strategic goal of value-based healthcare that is informed by the ultimate end of the common good.

(Premise 10) Value-based healthcare (generated by sufficient quality at affordable cost scaled to just societal distribution) requires the critical mass, durable, and institutionalized consensus of ecosystem partners on a unifying moral interoperability that informs the transparent, trustworthy, and reliable data interoperability for the AI-enabled digitalized ecosystem (leveraging throughout its network of such technologies as AI-augmented CS) to effective and efficiently deliver such value-based healthcare.

(Premise 11) This moral interoperability underlying the world's diverse religiously unaffiliated and affiliated belief systems (embodied in the health ecosystem and the competing, collaborating, and conflicting political ecosystem models in and among which they operate societally) rests on the individual dignity of

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each patient as a person and the resultant respect due to diverse cultures, both of which are nourished, safeguarded, and fulfilled in the common good (understood both in its Global Western-dominated approach to it via individual dignity and its Eastern/Southern-dominated approach to it via human and national security undermined longitudinally without it).

(Conclusion) Therefore, clinical, economic, and ethical justification from both dignity and security perspectives supports enhanced healthcare policy focus and healthcare system investment reducing disparities in CS particularly through the use of AI-augmentation in the AI-accelerated global digital health ecosystem, realized with the moral interoperability and data interoperability key to advancing healthcare to the shared, unifying, and real destination of the common good (which ecosystems advance toward in its dimension of health in particular) (Figure 1).

4. Discussion

This is the first known AI and Bayesian-augmented computational ethical and policy analysis integrating clinical, cost effectiveness, and healthcare disparity analyses with nationally representative data to estimate the global cost of healthcare disparities in CS and the savings from AI-enabled CS to reduce them. It suggests that reversing racial disparities particularly for Hispanics and Asians may save healthcare systems and nations globally $17.61 billion annually, with AI-augmented CS potentially contributing $625.40 million for Hispanics and $289.00 million for Asians in particular. The above findings support the cost savings imperative for such strategic and capacity-building investment in these AI-driven measures to improve healthcare's SEEE strategic aims sustainability, effectiveness, efficiency, and equity. Such empirical results inform the larger global bioethical argument from the twin dimensions of dignity and secu-

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rity (rooted in the personalist, multicultural, and metaphysical account of the person as a member of the global human family) to highlight the AI ethical imperative to optimize the performance of the global digital health ecosystem. Such an instrumental end is a critical means of advancing toward the ultimate end of the common good, in which the individual good of each person is safeguarded and in which it finds her/his fulfillment working toward.

This study therefore utilizes AI-driven Computational Ethical and policy analysis or AiCE to demonstrate the following: (a) the feasibility of applying this integrated methodology as a seamless, embedded, liquid approach for healthcare systems; (b) its application for high-value add targeted areas of the health ecosystem (such as the high individual and societal costs of CRC for exponential resultant benefits particularly through enhanced prevention); (c) its compatibility with the AI-accelerated digitalization of the global health ecosystem; (d) how (c) above enables it to self-organize, adapt, and optimize itself iteratively in real-time for efficient and equitable delivery of value-based healthcare globally (especially for lower income and resource communities, systems, and states) in what has been described as the future's 'thinking healthcare system'.1,12 This overarching computational ethical and policy approach to clinical and operational workflows for healthcare systems has previously been shown to be able to be digitalized and mathematically translated to augment real-time decision-making for system executives and clinicians:

$$AI\ Health_{Mathematical} = \left(\mathrm{HealthBD} \times \left[\overline{Delivery} + \sum_{n=1}^{\infty}\{\mathrm{PrMed}\ \langle\cos Delivery\rangle + \mathrm{PubHealth}\ \langle\sin Delivery\rangle\}\right]\right)^{AI-VBHC}$$

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Prior work has mapped how this 'AI Health' (that is trustworthy machine learning and deep learning-based co-designed) is the product of healthcare Big Data (HealthBD) and modern healthcare delivery (generated by PrMed or personalized medicine and PubHealth or public health) raised to the power of AI-VBHC or AI-enabled Value-Based Healthcare. Human dignity and security are thus digitalized into system operations at the fundamental mathematical level of algorithm creation and self-adaptation, thus integrated with EHRs for clinical operations and business dashboards for executive or organizational operations. AI-VBHC additionally has been shown to be produced as the product of AiCE, healthcare AI (both clinical and operational) and value-based healthcare (drawing on Porter and Teisberg's 2006 definition refined by the European Commissions' emphasis on equity):

$$\mathrm{AI}-\mathrm{VBHC} = AiCE \times ([Clinical + Operational]_{AI}) \times \left(\frac{Quality_{Equity \times Personal \times Social \times Wellbeing}}{Cost_{Time \times Capacity \times Support}}\right)$$

Such methodological advances have been further simplified to produce the proposed healthcare system DNA or organic formula for the future's thinking healthcare system in which Health (H) is the product of AI (A) and equity (E) squared:

$$H = AE^2$$

Akin to Einstein's famous E = MC2 (where energy is the product of mass and the speed of light squared in a way that describes how energy and mass can be essentially interchangeable), this system DNA describes how 'human health' and 'artificial intelligence' can become interchangeable in a globalized, digitalized, but still divided world: human health depends on the efficient delivery of

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value-based healthcare at scale that therefore produces equitable outcomes through AI that reaches it optimized form (by becoming truly 'intelligent' and thus knowledge of the ultimate good (including for humanity in what classically was defined as wisdom as the primary object of philosophy) and good actions as the primary object of the philosophical subdiscipline of ethics). It does so by being bounded by ethical parameters in which dignity is digitalized and embedded in the technical optimization of algorithmic performance by ultimately being strategically orientated to the common good of the global human family. AI Health (in which AI-empowered value-based healthcare delivery with Big Data) advancing efficiency at scale (at the individual and population levels globally) can begin to approximate equity, indicating that systems' performance optimizing individual wellbeing has been achieved simultaneously at the population level, and so signals the attainment of mature AI-empowered healthcare that is equity exponentiated (generating orders of magnitude improvements in wellbeing with each additional growth unit of AI-driven equity). Therefore, in the future's thinking healthcare system, optimized health is optimized AI, the energy powering humanity's future in which our technology is ethically used for the common good without sacrificing that of the individual. The foundational moral interoperability (uniting the diverse belief systems of the diverse partners of the AI-accelerated global health ecosystem) therefore informs the supporting data interoperability framework of digitalizing ecosystem that reaches forward together toward this common strategic aim, destination, and good.

This paper's methodological and practical innovations toward this vision are therefore meant to build on the important recent advances in the global push for improving modern healthcare to be more worthy of the patients and patients we purport to serve, as we increasingly understand how the dignity of persons are honored when systems advance their health and the security of such individuals are safeguarded (collectively manifested with the national security of the societies they constitute at the state and global levels). The

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COVID-19 pandemic therefore has sped up such efforts by the who, United Nations, influential healthcare and regulatory bodies (including the internationally impactful US Centers for Medicare and Medicaid producing industry-leading healthcare AI regulations and standards), and a consensus of nations the world over to improve the data interoperability of their healthcare systems and public health systems, in which the different partners in the global healthcare ecosystem must have a basic level of digital compatibility (utilizing a common or standard data vocabulary, infrastructure, storage, computing, and strategic end to align their unique capacities with common individual benefit to sustain the ecosystem's partnerships) (38-39). If partners cannot 'talk' to each other, they cannot use their tools for a common purpose effectively. And there cannot be a common technical language and collaborative arrangements with a unifying purpose and ultimate end without a sufficiently substantive, efficacious, and foundational common moral vision encompassing a common moral language, methodology, and metaphysical account of the human person that informs such practical concepts and interactions. There have been important historic advances in this direction including with the 2020 Rome Call, European Union, and US Department of Defense early standard setting in AI ethics (followed by the more detailed 2021 who ethics standard) (15,40-42). Yet despite the significant successes achieving multi-sector international consensus on AI ethics, these advances nonetheless are limited in their substance and applicability—they specify vague principles that are difficult to operationalize within healthcare systems' daily operations in a way that can be done in a way that respects the real-world demands of systems to be real-time, adaptive, and detailed (including to resolve disagreements among competing moral claims, technical barriers, and competing societal forces). AiCE operationalizing the substantive PSC as demonstrated in this paper suggests a possible viable way forward that operates within the already globally dominant ethical framework of individual dignity and rights (particularly influential in the Global West) in a way that is still intelligible and

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convergent with the Global East and South's community and security focus), while recovering a more substantive methodology through a common metaphysical foundation (still intelligible and compelling for reasons inherent to the world's diverse religiously affiliated and unaffiliate belief systems), and yet can still operate in healthcare systems as with the concrete clinical use case of CS for CRC.

The PSC-informed AiCE methodology within the larger conceptual framework of AI Health is meant to therefore propose a global, comprehensive, integrated, and concrete approach to translate the important but still general principles of the 2021 who landmark report and similar into reliable, transparent, useful, defensible, equitable and therefore trustworthy healthcare AI performance. (1,12,16). Such performance is in turn meant to jumpstart the generally efforts to more satisfactorily address global hesitation with algorithms' reliability, which are often undermined by their hidden assumptions (both technical and ethical). A 2021 Pew Research report noted how approximately 70% of world-leading AI executives, policymakers, and researchers doubt healthcare AI and even AI more generally will be ethical or committed to the public or common good (43). Similar findings and concerns are echoed by the international AI standard setting by the IEEE (the world's largest technical professional organization), the US National Security Commission on AI, and Stanford University's Institute for Human-Centered Artificial Intelligence. The daunting challenges to ethical AI (generally including healthcare in particular) according to such influential voices include overshadowing drivers that make the push for ethical AI largely irrelevant and/or ineffective: (a) the AI arms race between the US and China (the world's biggest AI creators including their corporations, universities, and militaries) framing AI largely within military, economic, and/or technical competition for global dominance); (b) the primary focus of profit and/or societal influence or control of the above actors; (c) the nature of AI (with its ubiquitous, rapid, unpredictable, and already seismic societal influence internationally); (d) and the widespread recognition of 'ethical AI' lacking general

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consensus about its formal training, standards, and even definition. Consider the patient safety community which has admirably generated in the last two decades multiple high profile studies, societies, and programs internationally to address the shortcomings and even failures of healthcare safety. Yet despite decades, billions of dollars, and thousands of researchers and leaders, the community in its own assessment has failed to produce a peer-reviewed study showing meaningful and sustained improvement at the region-level of adverse medical events (44). Like patient safety efforts, just because ethical AI is internationally desirable does not necessarily mean that it works. Nor does it mean that AI ethics papers, books, and studies actually deliver on real-world, concrete, and longitudinal advances at scale. These sobering reflections may ultimately require us in the AI ethics community to honestly question if the reason AI algorithms have thus far been generally unreliable and untrustworthy at scale is because we have not questioned our assumptions (both technically in our research and interventions, and even more fundamentally our assumptions that the work we do and the way we do it is actually relevant, meaningful, defensible, or useful for patients, providers, and payors). Have we moved to far away from the patient's bedside or kitchen table? Do we need to return to the lived experience and reality of persons, populations, healthcare and humanity (and thus reverse engineer our means of advancing toward them by first letting them speak for themselves and their needs)? Could the PSC-informed AiCE methodology and growing use cases including most recently with CS and CRC here suggest how we can move at speed and scale shoulder-to shoulder with healthcare systems locally and globally to answer their pressing AI ethics questions now (and those that will come before they get here)?

This novel approach is particularly relevant for addressing the primary twin challenges to ethical AI in healthcare currently: profit and regulation. McKinsey's 2021 and 2022 global studies of leading AI firms (including vendors for healthcare systems) demonstrated how optimizing profit and regulatory compliance helps differentiate

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high versus lower performers through rigorous AI design thinking, continuous internal testing, and governance (including compliance-by-design for relevant ethical, legal, policy, and cybersecurity standards) (45-46). For organizations including healthcare systems to adapt and eventually achieve enterprise-wide mature AI, it must first boost revenue greater than its permissible costs, while staying compliant with the above rules placed on it. An added layer of complexity is the rapid and unpredictable nature of AI recently reflected by the 2022 updated guidance from the US Food and Drug Administration (FDA) about regulating AI as medical devices (including identification and predictive algorithms for high risk or high utilizers, early warning systems for patient deterioration, and clinical decision tools) (47). How do you regulate an AI algorithm that can rewrite its own code with new data? The FDA proposed solution is a "a total product lifecycle-based regulatory framework" that is flexible enough to anticipate and permit a defined breadth and depth of self-adaption for the AI (particularly its machine learning applications) while still being rooted enough in the objective legal and ethical mandates to ensure "safety and effectiveness." This paper therefore provides a novel demonstration of the end-to-end integrated approach of the PSC-informed AiCE methodology that features a co-design adaptive methodology (that reverse engineers from the end or destination of common good-informed value-based healthcare to the means of AI-driven healthcare delivery to attain it), balancing the SEEE imperatives for AI-driven value-based healthcare.

Considered in its totality, this methodological proof of concept supports how sufficient healthcare system efficiency requires embedded AI that is technically and organizationally end-to-end (where a complex machine learning and deep learning models learn all the steps between the initial input to final output phase to accelerate operational effectiveness in the value-based healthcare delivery pipeline and network of diverse actors within and aligned with healthcare systems). And sufficient societal equity requires embodied dignity and diversity within systems (through multicultural metaphysics

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as articulated by the PSC) that is epistemically end-to-end (horizontally and vertically integrating the applied sciences of data science and clinical science with their underlying political economic intermediary layer and their underlying layer of the theoretical science of metaphysics). Yet there are no other known operational let alone integrative conceptual frameworks that define, defend, and deploy such AI (let alone in healthcare systems or in healthcare regulation at the system, professional, payor, or government levels). This study therefore utilized AiCE within the AI Health framework for the use case of CS to conduct a global assessment for such an end-to-end AI architecture (in its moral, technical, and organizational dimensions). By digitalizing human dignity, this AiCE approach seeks to mathematically and practically maximize value-based healthcare (as quality divided by cost), individual human dignity (with related population diversity demographically and culturally and its community dimension of security), and patient safety (with related data security) while minimizing inequities, cost, waste, fraud, and cyberattacks to ultimately strengthen earned global societal trust in AI-enabled healthcare systems.

This study should still be interpreted cautiously in the context of its limitations, including its retrospective non-randomized NIS and global data, reliance on CS simulations, and broad range of topics in a condensed space. Additionally, it is focused on CS which is more readily available and prevalent in high- and higher middle-income countries and communities; additionally analyses are thus required to clarify the applicability of these results compared to alternative interventions in low middle- and low-income countries and how they can be made more readily available there (which is a part of a larger diffusion of innovation challenge in modern healthcare where more expensive technologies and medications have a notable lag time from where they are often first developed and deployed in higher income countries and when they are more readily available in lower income countries). This study sought to reduce the bias (and thus threats to internal and external validity) such limitations can

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introduce to the paper by deploying a novel methodology that is rigorous (integrating AI, Bayesian, and propensity score analytics), comprehensive (integrating clinical, cost, disparity, and ethical analyses), relevant (co-designed by data scientists, clinicians, ethicists, and executives to embed ethical AI through end-to-end integration with continuous healthcare system operations in both organizational and clinical workflows), transparent (explicitly specifying its metaphysical, multicultural, and historical assumptions, context, and extensive detail of its methodology including across three original books), and practical (respecting the real-world unethical impossibility of waiting for global randomization with CS and AI to inform current healthcare needs for ethical and policy guidance in this context).

5. Conclusion

This is the first known AI and Bayesian-augmented global and comprehensive computational ethical and policy analysis (integrating clinical, cost, disparity, and ethical analyses) including of CS for CRC. It demonstrates the novel findings of the upwards of $4 billion saved through AI-enabled CS, particularly to help reduce the $17.61 billion cost of racial disparities for Hispanics and Asians not explained sufficiently by clinical factors. Through this concrete use case, this paper introduces the novel concept of 'moral interoperability' as potentially the critically needed foundation for the data interoperability-based Big Data architecture of the AI-driven digitalization global health ecosystem (spanning our world's diverse healthcare systems, belief systems, cultures, and multi-sector actors). This paper thus proposes how healthcare AI algorithms may become reliable (through such a comprehensive methodology embedded and iteratively self-adapting in real-time in real-world healthcare systems) while becoming more trustworthy (to provide a blueprint, roadmap, and even DNA for how modern healthcare systems can function efficiently and equitably as the future's thinking healthcare system by honoring human

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dignity, security, and the common good-empowering such instrumental technical and ethical interoperability).

References

1. Monlezun DJ. The Thinking Healthcare System: Artificial Intelligence and Human Equity. Oxford, UK: Elsevier. 2023.
2. McGlynn EA, Asch SM, Adams J. The quality of health care delivered to adults in the United Nations. New England Journal of Medicine. 2003; 348:2635-2645. https://pubmed.ncbi.nlm.nih.gov/12826639/
3. WHO, OECD, World Bank, 2018. Delivering quality health services: A global imperative for universal health coverage. Geneva, Switzerland: who Press.
4. Makary MA. Daniel M. Medical error-the third leading cause of death in the US. BMJ. 2016; 353:i2139. https://doi.org/10.1136/bmj.i2139
5. Barber SL, Lorenzoni L, Ong P. Price setting and price regulation in health care. Geneva, Switzerland: who Press. 2019.
6. Shamasunder S, Holmes SM, Goronga T, Carrasco H, Katz E, Frankfurter R. COVID-19 reveals weak health systems by design: Why we must re-make global health in this historic moment. Global Public Health. 2020; 15(7):1083-9. https://doi.org/10.1080/17441692.2020.1760915
7. Appleby C, Hendricks J, Wurz J, Shudes C, Shukla M, Chang C. Digital transformation: from a buzzword to an imperative for health systems. Deloitte. 2020. https://www2.deloitte.com/uk/en/insights/industry/health-care/digital-transformation-in-healthcare.html
8. Chén OY, Roberts B. Personalized health care and public health in the Digital Age. Frontiers in Digital Health. 3:595704. https://doi.org/10.3389/fdgth.2021.595704
9. Zimlichman E, Nicklin W, Aggarwal R, Bates DW. Health care 2030: The coming transformation. New England Journal of Medicine Catalyst. 2020. https://catalyst.nejm.org/doi/full/10.1056/CAT.20.0569
10. Philips. Future Health Index 2021: A resilient future. 2021. https://www.philips.com/c-dam/corporate/newscenter/global/future-health-index/report-pages/experience-transformation/2021/philips-future-health-index-2021-report-healthcare-leaders-look-beyond-the-crisis-global.pdf
11. Takemi K, Jimba M, Ishii S, Katsuma Y, Nakamura Y. Working Group on Challenges in Global Health and Japan's Contribution. Human security approach for global health. London, England: Lancet. 2008; 372(9632):13-14. https://doi.org/10.1016/S0140-6736(08)60971-X
12. Monlezun DJ, Sinyavskiy O, Peters N, Steigner L, AksamitT, Girault MI, Garcia A, Gallagher C, Iliescu C. Artificial Intelligence-Augmented Propensity Score, Cost Effectiveness and Computational Ethical Analysis of Cardiac Arrest and Active Cancer with Novel Mortality Predictive Score. Medicina Kaunas, Lithuania. 2022; 58(8):1039. https://doi.org/10.3390/medicina58081039

https://doi.org/10.36105/mye.2024v35n4.02

13. Gomez J, Feldberg B, Krois J, Schwendicke F. Evaluation of the Clinical, Technical, and Financial Aspects of Cost-Effectiveness Analysis of Artificial Intelligence in Medicine: Scoping Review and Framework of Analysis. JMIR Med Inform. 2022; 10(8):e33703. https://doi.org/10.2196/33703
14. Voets MM, Veltman J, Slump CH, Siesling S, Koffijberg H. Systematic Review of Health Economic Evaluations Focused on Artificial Intelligence in Healthcare: The Tortoise and the Cheetah. Value in health: the journal of the International Society for Pharmacoeconomics and Outcomes Research. 2022; 25(3):340–349. https://doi.org/10.1016/j.jval.2021.11.1362
15. who, 2021. who issues first global report on artificial intelligence (AI) in health and six guiding principles for its design and use. World Health Organization. https://www.who.int/news/item/28-06-2021-who-issues-first-global-report-on-ai-in-health-and-six-guiding-principles-for-its-design-and-use
16. Monlezun DJ. The Personalist Social Contract: Saving Multiculturalism, Artificial Intelligence & Civilization; Cambridge Scholars Press: Cambridge, UK, 2022.
17. Morgan E, Arnold M, Gini A, Lorenzoni V, Cabasag CJ, Laversanne M, Vignat J, Ferlay J, Murphy N, Bray F. Global burden of colorectal cancer in 2020 and 2040: incidence and mortality estimates from GLOBOCAN. BMJ gut. 2022. https://doi.org/10.1136/gutjnl-2022-327736
18. HCUP Databases. Healthcare Cost and Utilization Project (HCUP): Agency for Healthcare Research and Quality. 2021. www.hcup-us.ahrq.gov/nisoverview.jsp
19. DUA Training. Healthcare Cost and Utilization Project (HCUP): Agency for Healthcare Research and Quality. 2021. www.hcup-us.ahrq.gov/DUA/dua_508/DUA508version.jsp
20. Data Sets Not Requiring IRB Review. National Bureau of Economic Research. 2022. https://www.nber.org/programs-projects/projects-and-centers/human-subjects-protection-and-institutional-review-board-irb/guidance-data-sets-not-requiring-irb-review
21. Monlezun DJ, Lawless S, Palaskas N, Peerbhai S, Charitakis K, Marmagkiolis K, Lopez-Mattei J, Mamas M, Iliescu C. Machine learning-augmented propensity score analysis of percutaneous coronary intervention in over 30 million cancer and non-cancer patients. Front. Cardiovasc. Med. 2021; 8:620857.
22. Monlezun DJ, Carr C, Niu T, Nordio F, DeValle N, Sarris L, Harlan T. Meta-analysis and machine learning-augmented mixed effects cohort analysis of improved diets among 5847 medical trainees, providers and patients. Public Health Nutr. 2022; 25:281-289.
23. Murray TA, Yuan Y, Thall PF. A Bayesian Machine Learning Approach for Optimizing Dynamic Treatment Regimes. Journal of the American Statistical Association. 2018; 113(523):1255-1267. https://doi.org/10.1080/01621459.2017.1340887
24. D’Agostino RB. Propensity score methods for bias reduction in the comparison of a treatment to a non-randomized control group. Stat. Med. 1998; 17: 2265-2281. https://pubmed.ncbi.nlm.nih.gov/9802183/
25. Elze MC, Gregson J, Baber U, Williamson E, Sartori S, Mehran R, Nichols M, Stone GW, Pocock SJ. Comparison of propensity score methods and covariate

adjustment: Evaluation in 4 cardiovascular studies. J. Am. Coll. Cardiol. 2017; 69:345357. https://doi.org./10.1016/j.jacc.2016.10.060
26. Wager E, Ortaliza J, Cox C. How does health spending in the U.S. compare to other countries? Perseon-KFF. 2022. https://www.healthsystemtracker.org/chart-collection/health-spending-u-s-compare-countries/#GDP%20per%20capita%20and%20health%20consumption%20spending%20per%20capita,%202020%20(U.S.%20dollars,%20PPP%20adjusted
27. U.S. Population Estimated at 332,403,650 on Jan. 1, 2022. U.S. Department of Commerce. 2022. https://www.commerce.gov/news/blog/2022/01/us-population-estimated-332403650-jan-1-2022#:~:text=As%20our%20nation%20prepares%20to,since%20New%20Year%E2%80%99s%20Day%202021
28. Tikkanen R, Abrams MK. U.S. Health Care from a Global Perspective, 2019: Higher Spending, Worse Outcomes? The Commonwealth Fund. 2020. https://www.commonwealthfund.org/publications/issue-briefs/2020/jan/us-health-care-global-perspective-2019
29. World population to reach 8 billion on 15 November 2022. United Nations. 2022. https://www.un.org/en/desa/world-population-reach-8-billion-15-november-2022
30. Distribution of the global population. Statista. 2022. https://www.statista.com/statistics/237584/distribution-of-the-world-population-by-continent
31. Cost-benefit analysis. Centers for Disease Control and Prevention. 2022. https://www.cdc.gov/policy/polaris/economics/cost-benefit/index.html
32. Areia M, Mori Y, Correale L, Repici A, Bretthauer M, Sharma P, Taveira F, Spadaccini M, Antonelli G, Ebigbo A, Kudo SE, Arribas J, Barua I, Kaminski MF, Messmann H, Rex DK, Dinis-Ribeiro M, Hassan C. Cost-effectiveness of artificial intelligence for screening colonoscopy: a modelling study. The Lancet. Digital health. 2022; 4(6):e436–e444. https://doi.org/10.1016/S2589-7500(22)00042-5
33. Monlezun DJ, Sotomayor C, Peters N, Steigner L, Gallagher C, Garcia A. The global AI ethics of COVID-19 recovery: Narrative review and personalist social contract ethical analysis of AI-driven optimization of public health and social equities. Med. Eth. 2022; 33: 357-376. https://doi.org/10.36105/mye.2022v33n2.02
34. Aristotle. Metaphysics. In The Basic Works of Aristotle; McKeon, R., Ed.; ~323 B.C., bk. XII; The Modern Library: New York. 2001; Chapter 9.
35. Schaeffer M. Thomistic Personalism: Clarifying and Advancing the Project; York University Press: Canada. 2016.
36. Clarke NW. Person and Being; Marquette University Press: Milwaukee, WI, USA, 1993.
37. Aquinas, T. The Summa Theologica; (1274), I.5.1, I.29.3, Ia-IIae.61.2; IIi.58.3, I.44.4; Benziger Brothers: USA. 1947.
38. Siwicki, B., 2021. Data interoperability, knowledge interoperability and the learning health system. Healthcare IT News. https://www.healthcareitnews.com/news/data-interoperability-knowledge-interoperability-and-learning-health-system
39. Brooks-LaSure C. Interoperability and the connected health care system. Centers for Medicare & Medicaid Services. 2021. https://www.cms.gov/blog/interoperability-and-connected-health-care-system

https://doi.org/10.36105/mye.2024v35n4.02

40. FAO. Rome call for artificial intelligence ethics draws global interest. United Nations Food and Agriculture Organization. 2020. https://www.fao.org/newsroom/detail/Rome-Call-for-Artificial-Intelligence-ethics-draws-global-interest/en
41. EU, 2020. On artificial intelligence: A European approach to excellence and trust. European Union. https://ec.europa.eu/info/sites/default/files/commission-white-paper-artificial-intelligence-feb2020_en.pdf
42. DoD, 2020. DOD adopts ethical principles for artificial intelligence. US Department of Defense. https://www.defense.gov/News/Releases/Release/Article/2091996/dod-adopts-ethical-principles-for-artificial-intelligence
43. Rainie L, Anderson J, Vogels EA. Experts doubt ethical AI design will be broadly adopted as the norm within the next decade. Pew Research Center. 2021. https://www.pewresearch.org/internet/2021/06/16/experts-doubt-ethical-ai-design-will-be-broadly-adopted-as-the-norm-within-the-next-decade
44. Schiff G, Shojania KG. 2022. Looking back on the history of patient safety: An opportunity to reflect and ponder future challenges. BMJ Quality & Safety. 2022; 31(2): 148-52.
45. Chui M, Hall B, Singla A, Sukharevsky A. The state of AI in 2021. McKinsey & Co. 2022 https://www.mckinsey.com/capabilities/quantumblack/our-insights/global-survey-the-state-of-ai-in-2021
46. Chui M, Hall B, Mayhew H, Singla A. The state of AI in 2022. McKinsey & Co. https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai-in-2022-and-a-half-decade-in-review
47. FDA. Clinical decision support software: Guidance for industry and Food and Drug Administration Staff. US Food and Drug Administration. 2022. https://www.fda.gov/media/109618

https://doi.org/10.36105/mye.2024v35n4.02