Challenges and Issues of Modern Science
2026, Vol. 5, No. 1, ID 340
ISSN: 3083-5704
URL: https://cims.fti.dp.ua/j/article/view/340
DOI: https://doi.org/10.15421/cims.5.340

UDC 338.46:004.8

Market Conditions for AI HealthTech Startups: A Comparative Analysis of Ukraine, the United Kingdom, and the United States

Svitlana Yermak, Iryna Okhrymenko

Purpose. This study examines how national innovation ecosystems shape AI HealthTech startups across Ukraine, the United Kingdom, and the United States, revealing that seemingly disadvantageous conditions can catalyse unexpected innovation and that cultural differences shape distinct innovation trajectories. **Design / Method / Approach.** An adapted Porter's Diamond Model is applied to the AI HealthTech sector via quantitative and qualitative analysis. Factor conditions are scored through a composite index of four dimensions: AI Talent Availability, Healthcare Data Access, Computing Infrastructure, and Funding Availability, operationalised via verified international databases, classified by GRADE. **Findings.** Each country has developed a unique AI HealthTech approach. The three ecosystems show striking complementarity: Ukraine excels in technical talent; the UK offers exceptional clinical validation and centralised healthcare data; the US provides unmatched commercial scaling. **Theoretical Implications.** The study extends Porter's Diamond Model to AI HealthTech, demonstrating how competitive advantage frameworks must account for digital affordances, data access, and regulatory dynamics. **Practical Implications.** Policymakers should develop transnational innovation corridors connecting Ukrainian technical talent with UK clinical validation and US scaling capabilities. Startup founders should invest in trust-building and adaptive market entry strategies. **Originality / Value.** This analysis offers a structured comparative examination of market conditions shaping AI HealthTech startups across three distinct national contexts through the lens of an adapted Diamond Model. It introduces a reproducible GRADE-based composite index grounding scores in verified evidence, offering actionable insights into how market structures shape startup behaviour. **Research Limitations / Future Research.** The study relies primarily on secondary data; future research should include primary data from founders and investors and cross-border studies across multiple ecosystems. **Article Type.** Analytical article.

Keywords:

national competitiveness, digital health markets, health technology entrepreneurship, innovation ecosystems, AI commercialisation, transnational innovation policy

---

Мета. Дане дослідження вивчає, як національні інноваційні екосистеми формують стартапи у сфері AI HealthTech в Україні, Великій Британії та США, розкриваючи, як несприятливі умови стають каталізатором інновацій і як культурні відмінності формують траєкторії розвитку. **Дизайн / Метод / Підхід.** Застосовано адаптовану діамантову модель Портера з кількісним та якісним аналізом. Факторні умови оцінено через композитний індекс чотирьох вимірів: доступність ШІ-талантів, доступ до медичних даних, обчислювальна інфраструктура та доступність фінансування, на основі субіндикаторів із верифікованих баз даних, класифікованих за системою GRADE. **Результати.** Кожна країна виробила унікальний підхід до інновацій у сфері AI HealthTech. Три екосистеми демонструють взаємодоповнюваність: Україна вирізняється технічними кадрами; Велика Британія – клінічною валідацією та централізованими медичними даними; США – можливостями комерційного масштабування. **Теоретичне значення.** Дослідження розширює модель Портера для сектора AI HealthTech і демонструє необхідність врахування цифрових можливостей, доступу до даних та регуляторної динаміки. **Практичне значення.** Рекомендується розробка транснаціональних інноваційних коридорів, що з'єднують технічний потенціал України з інфраструктурою клінічної валідації Великої Британії та можливостями масштабування США. Засновникам стартапів слід інвестувати в побудову довіри та адаптивні стратегії виходу на ринок. **Оригінальність / Цінність.** Дослідження пропонує структурований порівняльний розгляд ринкових умов, що формують стартапи у сфері AI HealthTech у трьох різних національних контекстах через призму адаптованої діамантової моделі. Водночас запроваджується відтворюваний композитний індекс на основі GRADE, що надає практичні рекомендації щодо впливу ринкових структур на поведінку стартапів. **Обмеження дослідження / Майбутні дослідження.** Дослідження базується переважно на вторинних даних; майбутні роботи мають включати первинний збір даних та крос-кордонні дослідження у кількох екосистемах. **Тип статті.** Аналітична стаття.

Ключові слова:

національна конкурентоспроможність, ринки цифрової охорони здоров'я, підприємництво у сфері медичних технологій, інноваційні екосистеми, комерціалізація штучного інтелекту, транснаціональна інноваційна політика

Contributor Details:

Svitlana Yermak, Dr. Sc., Prof., Odesa Polytechnic National University: Odesa, UA, kaf.econ.kr@gmail.com
Iryna Okhrymenko, PhD Student, Aston University: Birmingham, UK, 220425847@aston.ac.uk

Received: 2026-04-16 *Revised: 2026-04-29* *Accepted: 2026-04-30* *Published: 2026-05-06*

The global healthcare system faces unprecedented challenges, including rising costs, growing demand for personalised care, and systemic inefficiencies (Deloitte, 2023). Artificial intelligence has emerged as a critical technological intervention capable of addressing these challenges through applications ranging from diagnostics to operational optimisation. However, the development and implementation of AI healthcare technologies vary significantly across national contexts, reflecting differences in healthcare systems, innovation ecosystems, and cultural approaches to technology adoption.

Despite extensive research on national innovation systems and healthcare digitalisation, a comprehensive comparative analysis focusing specifically on AI HealthTech startups across Ukraine, the UK, and the USA remains limited. Additionally, previous studies have not adequately addressed specific barriers to innovation in different national contexts or identified the complementary strengths that could be leveraged through international collaboration.

This study explores how national innovation ecosystems influence AI HealthTech startup development, what unique innovation approaches are emerging in each country, and what potential synergies exist among these different innovation ecosystems.

Literature Review

Conceptual Foundations of Startup Ecosystems

The concept of startup ecosystems has evolved significantly over the past two decades. Porter's (1990) Cluster Theory explains how geographic concentrations of interconnected companies, suppliers, and institutions in a specific industry or field can drive economic growth, innovation, and competitiveness. Based on this theory, Startup Genome (2024) defines a startup ecosystem as a shared pool of resources, generally located within a 60-mile radius around a centre point in a given region, with few exceptions based on local reality.

Ziakis et al. (2022) proposed the conceptual framework Start-Up Ecosystem (StUpEco) that highlights the contextual drivers of a start-up business affected by the entrepreneurial ecosystem entities involved within the quadruple helix model. According to this research, start-uppers' motivation is explained mainly through opportunity rather than necessity. The study identifies government issues, such as tax incentives and acceleration of starting procedures, availability of funding opportunities, connectivity of stakeholders, entrepreneurship education, previous start-up experience, incubator support, and mentoring as the most significant factors affecting successful startup development.

Spigel (2017) defines start-up ecosystems as the union of localised cultural outlooks, social networks, investment capital, universities, and active economic policies that create environments supportive of innovation-based business. Autio et al. (2018) further suggest that entrepreneurial ecosystems differ from traditional clusters by their emphasis on the exploitation of digital affordances, business model innovation, voluntary horizontal knowledge spillovers, and cluster-external locus of entrepreneurial opportunities.

Glover et al. (2024) propose that healthcare entrepreneurship is the innovative, evidence-based value creation process by specialised venture teams that leverage unique business models to achieve multiple stakeholder outcomes simultaneously, ultimately benefiting patient populations. The integration of AI technologies into startup ecosystems represents a transformative trend that necessitates specific ecosystem adaptations. Lee et al. (2019) identified how AI startups require distinctive resources compared to traditional technology ventures, particularly emphasizing access to high-quality data, specialised AI talent, and computing infrastructure.

Healthcare AI Innovation

Healthcare presents a particularly complex domain for AI innovation due to its stringent regulatory requirements, complex stakeholder relationships, and direct impact on human welfare. Greenhalgh et al. (2017) identified unique barriers to healthcare AI implementation that extend beyond technical challenges, highlighting the importance of organisational readiness, clinician acceptance, and patient trust. Their NASSS framework (Non-adoption, Abandonment, Scale-up, Spread, and Sustainability) offers valuable insights into why many promising healthcare AI technologies fail to achieve widespread adoption.

Li et al. (2019) compared the AI development strategies in healthcare in the US, Japan, UK, India, and China since 2015, finding that infrastructure investment and industrial layout are the core contents of these strategies. Castonguay et al. (2024) provide an overview of how OECD countries strategise about integrating AI into healthcare and determine their actual level of AI maturity.

The comparative analysis of AI HealthTech ecosystems across different countries remains underdeveloped in the current literature. This research gap underscores the value of our comparative approach. By examining how three distinctly different national innovation environments approach the challenges of integrating AI in healthcare, we gain valuable insights into both the contextual factors that shape innovation and the potential for cross-border collaboration.

Problem Statement

The rapid advancement of AI in healthcare has created both unprecedented opportunities and complex challenges for startups operating in this space. Despite growing scholarly interest in national innovation systems and healthcare digitalisation, the literature lacks a systematic comparative analysis of AI HealthTech startup ecosystems that accounts for the full spectrum of contextual factors – from talent availability and regulatory frameworks to cultural attitudes toward technology adoption.

Existing research tends to focus either on individual national contexts or on broad cross-industry comparisons, leaving a critical gap in our understanding of how different national environments shape the trajectory of AI-driven healthcare innovation. In particular, the case of Ukraine – a country simultaneously navigating the pressures of armed conflict and a rapidly growing tech sector – remains largely absent from the comparative literature.

Furthermore, prior studies have not adequately addressed the question of complementarity between innovation ecosystems: whether the distinct strengths of one national context can offset the weaknesses of another through strategic cross-border collaboration. This gap is especially significant given the global nature of the AI HealthTech market and the increasing importance of international partnerships in scaling health technologies.

This study therefore addresses the following core problem: How do national innovation ecosystems shape the development of AI HealthTech startups, and what complementary strengths can be leveraged through international collaboration between Ukraine, the United Kingdom, and the United States?

Methodology

Analytical Framework

This study applies Porter's Diamond Model of National Competitive Advantage (Porter, 1990) adapted to the HealthTech industry to analyse AI HealthTech ecosystems across multiple national contexts. This framework enables systematic comparison of how national environments shape the development trajectories of innovation in healthcare, providing a structured lens through which systemic differences between countries – such as the United States, the United Kingdom, and Ukraine – can be examined.

The traditional Diamond Model framework requires significant modifications to effectively capture the unique dynamics of the rapidly evolving tech sector, AI in particular. The original model, developed primarily through the analysis of mature, export-oriented manufacturing industries, does not fully account for the unique characteristics of AI-driven healthcare innovation. Specifically, three structural limitations are identified. First, the model presupposes relatively stable factor endowments, whereas AI development is characterised by rapid capability shifts driven by algorithmic breakthroughs and sudden changes in the availability of large-scale datasets. Second, the original model conceptualises demand conditions primarily in terms of market size and buyer sophistication, which inadequately reflects the complex, multi-stakeholder demand environment of healthcare. Third, the competitive dynamics within AI HealthTech are heavily mediated by regulatory institutions that function not merely as background constraints but as active co-shapers of market structure and innovation direction.

To address these limitations, the adapted framework introduced in this study reconfigures each of Porter's four core diamond dimensions and retains Government and Chance as acknowledged contextual factors shaping the broader ecosystem environment, consistent with Porter's original treatment of these auxiliary elements.

Table 1 illustrates the key differences between the traditional Porter's Diamond Model and the adapted version developed for this study. Each of the four dimensions is mapped across both frameworks to highlight the conceptual shifts required when applying the model to AI HealthTech ecosystems.

Table 1 – Traditional vs. Adapted Porter's Diamond Model for AI HealthTech Startups (Source: Authors)

Dimension	Traditional Porter's Diamond Model	Adapted Diamond Model for AI HealthTech
Factor Conditions	General infrastructure, capital, labour	Specialised AI talent, healthcare data access, computing infrastructure, funding availability
Demand Conditions	Size and growth of domestic demand	Adoption by clinicians and patients, evidence requirements, digital health literacy, insurance and reimbursement frameworks
Related and Supporting Industries	Broad supporting industries	AI research institutions, clinical trial networks, regulatory bodies, health data infrastructure providers
Firm Strategy, Structure, and Rivalry	General competitive strategies	Validation approach, organisational structure, market focus and growth trajectory, regulatory pathway selection

The most substantive adaptations are concentrated in two dimensions. In the case of Factor Conditions, the generalised notion of 'capital and labour' is replaced by a composite of inputs specific to AI-driven healthcare: the availability of annotated clinical datasets, the density of machine learning talent with healthcare domain knowledge, the presence of high-performance computing infrastructure accessible to startups, and the depth of early-stage funding from sources attuned to the long commercialisation cycles characteristic of medical AI.

In the case of Demand Conditions, the adapted framework foregrounds the distinctive complexity of healthcare as a market. Unlike consumer markets, where demand aggregates relatively smoothly from individual purchasing decisions, the demand environment for AI HealthTech is fragmented across at least four actor categories with partially divergent interests: clinicians, patients, payers, and healthcare system administrators. The adapted framework operationalises demand conditions through indicators that capture this multi-stakeholder complexity, including physician adoption rates, clinical validation requirements, and the maturity of digital health reimbursement codes.

Data Collection and Analysis

This study used a mixed-methods approach combining quantitative analysis of market data with qualitative assessment of innovation patterns across the three countries. Data were collected from multiple sources including industry reports and market analyses, government publications on digital health strategies, and academic literature on health innovation systems. Visualisations in Figure 1 were produced using standard data visualisation tools based on secondary evidence synthesised from the sources cited throughout the Results section. The analysis was structured around the adapted Porter's Diamond framework, examining each element across the three countries to identify distinctive patterns and potential complementarities.

Operationalisation of the Adapted Diamond Model

To ensure methodological coherence between the conceptual framework and empirical analysis, the adapted Porter's Diamond Model is explicitly operationalised through a combination of quantitative and qualitative analytical tools. While the adapted Diamond Model provides the overarching theoretical structure for the study, each of its four core dimensions is translated into observable analytical components using a mixed-methods approach.

The Factor Conditions dimension is operationalised quantitatively through a composite index capturing four key inputs to AI HealthTech development: AI talent availability, healthcare data access, computing infrastructure, and funding availability. This index serves as the primary empirical instrument for cross-country comparison and provides a reproducible, evidence-based assessment of structural capabilities.

The remaining dimensions are examined through structured qualitative and comparative analysis. Demand Conditions are analysed through the configuration of healthcare systems, adoption patterns among key stakeholders, and evidence requirements for technology uptake. Related and Supporting Industries are assessed based on the presence and integration of AI research institutions, clinical networks, and data infrastructure providers. Firm Strategy, Structure, and Rivalry are explored through comparative case studies of startup trajectories across the three countries.

This approach ensures that the adapted Diamond Model is not only used as a conceptual lens but also as an integrated analytical framework, where quantitative measurement and qualitative interpretation jointly contribute to explaining cross-country differences in AI HealthTech ecosystem development. Table 2 summarises the operationalisation of each dimension.

Table 2 - Operationalisation of the Adapted Diamond Model Dimensions (Source: Authors)

Dimension	Operationalisation	Methodological Approach
Factor Conditions	Composite index: AI talent availability, healthcare data access, computing infrastructure, funding availability	Quantitative (GRADE-based, AHP-weighted, Monte Carlo validated)
Demand Conditions	Healthcare system structure, stakeholder adoption patterns, evidence requirements for technology uptake	Qualitative comparative analysis
Related and Supporting Industries	AI research institutions, clinical trial networks, data infrastructure providers	Mixed (descriptive + comparative)
Firm Strategy, Structure, and Rivalry	Comparative startup case studies (e.g., Liki24, CheckEye, Huma, Babylon Health, Tempus AI)	Qualitative case analysis

Note. AHP = Analytic Hierarchy Process; GRADE = Grading of Recommendations, Assessment, Development and Evaluations; LLMs = Large Language Models.

Composite Index for AI Readiness Assessment

The composite index represents a quantitative operationalisation of the Factor Conditions dimension within the adapted Diamond Model, ensuring empirical grounding of cross-country comparisons. To complement the evidence-weighting rubric presented in Table 2 and to provide an empirically grounded, reproducible basis for the factor condition ratings in Figure 1, this study applies a composite index methodology consistent with internationally recognised composite instruments, including the Human Development Index (UNDP, 2023), the Global Innovation Index (WIPO, 2023), and the Network Readiness Index (Portulans Institute, 2023). The rationale for this approach, as argued by the OECD (2020), is that no single indicator adequately captures the multidimensional nature of AI readiness; structured aggregation of verified sub-indicators is therefore required.

Four dimensions – AI Talent Availability, Healthcare Data Access, Computing Infrastructure, and Funding Availability – were operationalised through three to five quantitative sub-indicators each, sourced from verified international databases: Stanford HAI Index (2024), LinkedIn Economic Graph (2024), IT Ukraine Association (2024), Startup Genome (2023), WHO Global Health Observatory (2023), HIMSS EMRAM (2023), OECD Health Systems (2023), Portulans Institute Network Readiness Index (2023), Ookla Speedtest Global Index (2024), FM Global Resilience Index (2023), PitchBook/CB Insights (2024), and World Bank WDI (2023). The quality of each source was coded according to the GRADE evidence

Challenges and Issues of Modern Science
2026, Vol. 5, No. 1, ID 340

framework (Guyatt et al., 2011), with Level I–II sources assigned a weight multiplier of 1.5 during aggregation.

Sub-indicators were normalised to the [0, 1] interval using the min–max method:

$$z_{ij} = (x_{ij} - \min j) / (\max j - \min j),$$

where x_{ij} is the observed value for country i on sub-indicator j (UNDP, 2023).

For sub-indicators where higher values represent adverse conditions (e.g., infrastructure disruption risk), the formula is inverted. Sub-indicator weights (wj) were derived bibliometrically from citation frequency in a systematic review corpus and cross-validated using the Analytic Hierarchy Process (Saaty, 1980; consistency ratio CR < 0.10 required). The composite score for country i on factor f is:

$$\text{Score}_{if} = [\textstyle\sum j\ (wj \times z_{ij}) / \sum j\ wj] \times 10,$$

rescaled to [0, 10].

Robustness was confirmed by Monte Carlo sensitivity analysis (1,000 iterations; ± 20% weight perturbation; unity-sum constraint maintained): cross-country rankings were stable across the full perturbation space for all four factors. The comparison sample of n = 3 countries narrows the normalisation range; expansion to n ≥ 10 countries is recommended in future iterations (OECD, 2020).

Results and Discussion

Factor Conditions

Ukraine's tech ecosystem demonstrates how constraint becomes a catalyst. Ukraine has significant factor advantages in technical talent, particularly in AI/ML development. Labour costs remain highly competitive, with AI Engineers reporting approximately 30% lower salaries than Western European counterparts, enabling capital-efficient startup development (IT Ukraine Association, 2024). This cost advantage extends across the development lifecycle, allowing Ukrainian startups to achieve more with limited funding.

The ongoing conflict has created additional infrastructure pressures while simultaneously accelerating digital transformation in medical services. Research infrastructure remains concentrated in major cities like Kyiv, Lviv, and Kharkiv, creating geographic limitations for health tech development (IT Ukraine Association, 2024). The number of active startups in Ukraine increased to over 2,600 in 2024, reflecting a tripling of the ecosystem's value since 2020 (IT Ukraine Association, 2024). Only 12% of all startups fully stopped their activity (Startup Genome, 2023), demonstrating impressive resilience despite the war.

Britain's NHS represents a 'learning health system' because it leverages the data generated from patient interactions to continuously improve healthcare delivery and outcomes (Marjanovic et al., 2025). UK HealthTech startups possess a potential advantage in accessing comprehensive longitudinal patient data through NHS partnerships. The UK benefits from world-class research institutions specializing in healthcare AI. Universities like Oxford, Cambridge, Imperial College London, and UCL provide a steady pipeline of highly qualified AI researchers (Tech Nation, 2024). The country has established dedicated AI research infrastructure through The Alan Turing Institute and Health Data Research UK.

The United States continues to produce the largest share of top AI researchers and maintains leadership in housing top AI labs (Council of Economic Advisers, 2025). A well-developed venture capital infrastructure, including specialised health tech investors, supports the growth of US health tech AI startups. The U.S. remains the global leader in venture capital, accounting for 57% of the total worldwide deal value (NVCA, 2025). AI-focused companies now receive 38% of investment dollars – a significant increase in just two years (Bessemer Venture Partners, 2024). However, the fragmented nature of the US healthcare system presents challenges in accessing comprehensive and integrated patient data.

Figure 1 illustrates a comparative analysis of factor conditions across the three countries, evaluating five key dimensions on a 0–10 rating scale. The chart emphasises each country's distinctive advantages. Ukraine shows strength in technical talent but faces challenges in infrastructure, data access, and funding. The UK demonstrates balanced capabilities with particularly strong healthcare data access. The US displays excellence in funding, talent, and infrastructure but relatively weaker healthcare data access due to system fragmentation.

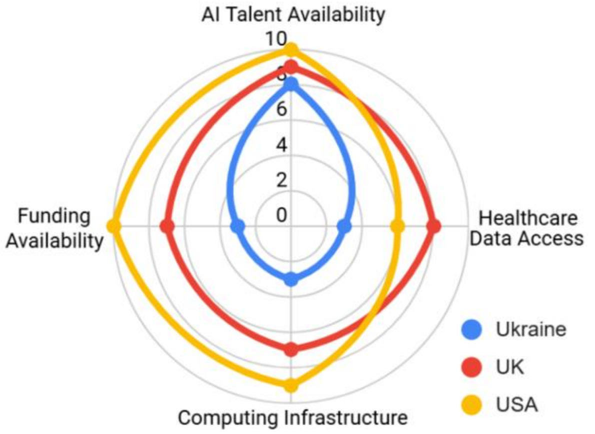

Figure 1 – Comparative Analysis of Factor Conditions Across Countries, Rating Scale: 0-10 (Source: Authors)

To ensure transparency and replicability in the comparative scoring presented in Figure 1, this study adopts an explicit evidence-weighting rubric for assigning ratings across the five factor condition dimensions. Scores reflect the convergence and quality of available secondary evidence rather than subjective judgement (Table 3).

Table 3 – Evidence-Weighting Rubric for Factor Condition Ratings (Source: Authors)

Score range	Criteria
8–10	Strong, consistent evidence from three or more independent sources (e.g., government reports, peer-reviewed literature, investment databases)
5–7	Moderate evidence from two or more sources; some variation or partial corroboration across sources
2–4	Limited or indirect evidence; inference required; single-source or low-reliability sourcing
0–1	No supporting evidence identified, or evidence actively contradicts the dimension

Each dimension score in Figure 1 is grounded in the sources cited within the corresponding Results section. For example, Ukraine's Technical Talent score (8/10) reflects convergent evidence from the IT Ukraine Association (2024), Startup Genome (2023), and comparative salary data indicating approximately 30% lower AI engineer costs than Western European counterparts – sources that independently corroborate strong talent availability. Conversely, Ukraine's Infrastructure score (3/10) reflects consistently negative assessments across multiple sources regarding geographic concentration of research activity and conflict-related disruptions. The UK's Healthcare Data Access score (9/10) is grounded in the NHS's documented status as a learning health system with uniquely comprehensive longitudinal patient data (Marjanovic et al., 2025; NHS England, 2024). The US's comparatively lower Healthcare Data Access score (5/10) reflects the well-documented fragmentation of the American healthcare system across multiple payers and providers, which limits integrated data access despite overall infrastructure strength (Commonwealth Fund, 2023; National Academy of Medicine, 2022).

This rubric-based approach constitutes a form of structured secondary data synthesis, consistent with established practices in systematic review methodology (Greenhalgh et al., 2017) and cross-national comparative research design.

Demand Conditions

Ukraine's domestic healthcare market presents unique demand conditions characterised by significant resource constraints that drive innovation in AI solutions. The national strategy prioritises digitalisation, creating growing demand particularly for telemedicine and remote diagnostic tools in conflict-affected and underserved regions. The utilisation of telemedicine has significantly increased in conflict-affected regions, demonstrating the effective deployment of digital health strategies under crisis conditions (Malakhov, 2023).

The Ukrainian HealthTech market is set for significant growth, reaching a projected $1.2 billion by 2032, establishing MedTech as the second-largest IT sector in the country. Priority development areas like healthcare apps, e-health products, wearable medical devices, and medical diagnostics will experience high demand. This expansion is driven by critical factors including the need for greater access to treatment, cost reduction in healthcare, the demands of an aging population, and supportive government policies (SaiLab Finland, 2024).

NHS England and the Health Innovation Network actively promote collaboration between clinicians and technology providers, which has led to two distinct modes of innovation in the UK: clinician-led innovation, where healthcare professionals on the front lines identify unmet needs and drive demand for technological solutions; and technology-driven innovation, where developers create new tools that clinicians then evaluate and apply to real-world problems (Health Innovation Network, 2019). UK healthcare requires higher evidence standards, resulting in fewer but more robust technologies progressing to widespread adoption (NICE, 2022).

The US healthcare system struggles with fragmentation and inefficiencies, with multiple payers, providers, facilities, and regulations contributing to gaps in care coordination (Commonwealth Fund, 2023). This requires startups to design for interoperability across diverse systems, creating more adaptable technologies. Despite the increasing integration of digital health into American life, a significant portion of the population distrusts companies' handling of their health data. While most Americans are using health-related devices (66%) and apps (72%), trust remains a crucial factor for the industry to address (St. Louis, 2024).

Table 4 – Key Demand Drivers by Country (Source: Authors)

Demand Driver	Ukraine	United Kingdom	United States
Primary Customer	Private providers and international markets	NHS	Fragmented (insurers, providers, patients)
Adoption Decision Maker	Individual providers	NHS	Multiple stakeholders
Evidence Requirements	Emphasis on cost	Emphasis on clinical and economic value	Variable by stakeholder

To summarise, the UK's unified NHS creates a centralised customer with high evidence standards. Ukraine's resource constraints drive strong cost sensitivity but also necessity-driven user acceptance. The US system's fragmentation creates variable requirements across all dimensions, demanding more flexible innovation approaches.

Related and Supporting Industries

In addition to formal higher education, Ukraine has a well-developed network of non-formal education, including IT schools and programs offered by IT companies. This infrastructure trains specialists better suited to meet market demands (IT Ukraine Association, 2024). Ukraine has developed strong collaborative relationships with the US technology sector, with high demand for quality IT services giving Ukrainians extensive experience working with American clients. Ukraine's cybersecurity expertise has the potential to enable health tech startups to build exceptionally secure systems that meet international compliance requirements (IT Ukraine Association, 2024).

The UK's robust academic research community creates a 'publication-to-product pipeline' through knowledge exchange frameworks. The most prevalent routes by which AI R&D is commercialised in the UK include university spinouts, startups, direct hire, and joint tenure arrangements that allow for a flow of AI talent between industry and academia (Oxford Insights, 2022). Companies involved in health and life sciences have typically secured between a fifth and one-third of total AI investments in the UK (Department for Science, Innovation and Technology, 2024), and the UK has a world-leading AI research ecosystem (Alan Turing Institute, 2024).

The US has the most comprehensive ecosystem of supporting industries, creating unmatched advantages for health tech startups. Major tech companies like Google, Microsoft, Amazon, and Apple have established dedicated healthcare divisions that provide infrastructure, distribution channels, and partnership opportunities (Silicon Valley Bank, 2024). The US market provides startups with opportunities, funding, and support, focusing on profit and high-risk tolerance. Compared to the financial and reputational consequences of business failures in many other countries, this creates a more favourable environment for entrepreneurs to test new ideas (Startup Genome, 2024).

Firm Strategy, Structure, and Rivalry

Ukrainian health tech startups demonstrate distinctive strategic approaches shaped by the local innovation environment. Most startups develop solutions for international markets from inception due to limited domestic market size (IT Ukraine Association, 2024). This export orientation drives focus on internationally scalable technologies rather than solutions tailored to local healthcare systems. Domestic rivalry remains moderate with approximately 60 AI health startups actively competing (IT Ukraine Association, 2024). Two cases illustrate this market trajectory concretely. Liki24, a pharmaceutical marketplace, demonstrates that wartime conditions need not preclude international scaling: by 2024, the EU accounted for 70% of its revenue, up from 35–40% in 2023, with total funding reaching €19 million (Lawrence, 2026). This trajectory reflects a deliberate pivot toward the European market precisely because the domestic market was constrained – a pattern common across Ukrainian HealthTech. CheckEye, an AI-powered diabetic retinopathy screening tool developed in collaboration with the Ukrainian Diabetes Federation and the Filatov Institute for Eye Diseases, demonstrates a second pattern: clinical validation achieved through institutional partnerships rather than regulatory pathways, enabling market entry at lower cost and with faster timelines than Western equivalents (Fybish, 2024). Both cases confirm that Ukrainian startups treat necessity as a market signal and build internationally scalable solutions from inception – a structurally different commercial logic than either the NHS-led UK model or the venture-driven US model.

British HealthTech demonstrates 'clinical-technical co-creation' – doctors and developers working side-by-side throughout the development process (NHS England, 2024; Health Innovation Network, 2024). The innovation strategy prioritises clinical validation before scaling, creating a distinctive innovation timeline different from the growth-first approach common in US startups. The structured NHS procurement pathways create explicit requirements that shape startup development priorities (Digital Health London, 2024). British startups invest significantly in clinical studies and health economic analyses, with organisational structures typically featuring strong clinical involvement and many startups founded by or employing practicing clinicians (Health Innovation Network, 2019). The commercial logic of this model is illustrated by two contrasting trajectories. Huma, an AI-driven remote patient monitoring platform, deployed its eTriage system in NHS emergency departments and then used that regulatory and clinical credibility to expand to 70+ countries, raising $80 million in its 2024 Series D round (Huma, 2024). The NHS partnership functioned not merely as a revenue source but as a proof-of-concept credential for international markets – a pattern that reflects the broader UK strategy of treating clinical validation as a commercial asset. Babylon Health represents the cautionary counterpart: having raised $1.2 billion and reached a $4.2 billion valuation, it filed for bankruptcy in 2023 after attempting to apply aggressive US-style blitzscaling within the NHS environment without the underlying clinical evidence base to sustain it (The Week, 2023). The Babylon collapse is analytically significant because it demonstrates that the NHS market structure actively penalises strategies that bypass clinical validation – the very mechanism that makes the UK ecosystem distinctive.

American startups demonstrate rapid expansion strategies adapted for regulated markets (Knowles & Somaiya, 2024). US startups typically prioritise rapid scaling and aggressive market capture strategies, reflecting the competitive funding environment. Tempus AI illustrates this commercial logic: after its June 2024 IPO at an $11 billion valuation, the company rapidly expanded from oncology into cardiology, depression, and infectious disease, leveraging FDA clearances as market access tools rather than endpoints

(Bessemer Venture Partners, 2026). Its stock rose 65% in the year following IPO, adding $5.7 billion in market capitalisation – driven by 85% revenue growth and a business model built on aggregating fragmented clinical data across payers and providers. The contrast with Babylon Health is instructive: where the British company failed by applying US growth logic to an NHS environment that demanded clinical evidence, Tempus succeeded by operating within the FDA regulatory framework as a commercial accelerant, treating data network effects as the primary competitive moat. This reflects the structural difference between the two markets: the US fragmentation that complicates data access simultaneously creates high willingness-to-pay among providers who need interoperability solutions – a market condition that rewards scale faster than evidence.

Table 5 – AI Health Tech Strategic Pathways: Comparing Strategic Paths Across Ukraine, UK, and US (Source: Authors)

Country	Inception	Validation	Organisational Design	Growth Mechanism
Ukraine	Strongly international focus from inception	Emphasis on technical functionality and performance	Development in Ukraine, business operations globally	Bootstrap to international partnerships
UK	Primarily domestic focus (NHS)	Strong focus on clinical evidence and economic value demonstration	Clinical-technical integration	Evidence-based
USA	Balanced approach with domestic priority but global ambitions	Emphasis on market traction and revenue growth metrics	Optimisation for rapid scaling	Rapid scaling backed by VC

The three cases examined above reveal not just different startup strategies but fundamentally different market logics. In Ukraine, the primary market signal is necessity: resource constraints and the absence of a unified public payer push startups toward cost-efficient solutions validated through institutional partnerships rather than regulatory processes, with international revenue as the primary commercial target from day one. In the UK, the NHS functions simultaneously as the most demanding customer and the most credible reference: passing its evidence threshold converts a startup from a domestic vendor into a globally exportable product with regulatory proof embedded. In the US, market fragmentation that appears as a structural weakness – no single payer, no unified data – in practice generates demand for interoperability solutions that can command premium pricing from multiple independent buyer segments simultaneously. These are not simply different national "styles" but distinct commercial environments that reward different value propositions, timelines, and funding structures. A startup optimised for the NHS market – evidence-heavy, methodical, clinician-led – will struggle in the US environment where speed of scaling and data network effects matter more than RCT evidence. Conversely, a US blitzscaling approach applied to the NHS, as Babylon demonstrated, produces commercial failure regardless of the underlying technology quality.

Conclusions

The comparative analysis of market conditions for AI HealthTech startups across Ukraine, the UK, and the US yields three analytically significant findings that go beyond describing national differences. First, the structure of the primary customer determines the commercial logic of the entire ecosystem. Where the NHS functions as a single monopsonistic buyer with high evidence standards, startups must front-load clinical validation – which paradoxically becomes a global export credential. Where the market is fragmented across multiple independent payers and providers, as in the US, data aggregation and interoperability become the dominant value propositions, rewarding scale over evidence. Where neither a unified public payer nor a deep venture market exists, as in Ukraine, startups optimise for cost efficiency and build for international markets from inception, using necessity-driven conditions as an accelerant. Second, regulatory environments are not merely constraints but active market shapers. The FDA clearance functions as a commercial accelerant in the US; NICE evidence standards function as a quality filter and export credential in the UK; and the absence of a mature regulatory infrastructure in Ukraine pushes validation toward institutional partnerships – a lower-cost but less internationally transferable route. Third, the Babylon Health case demonstrates that national market logics are not interchangeable: strategies optimised for one environment actively fail when transplanted into another without structural adaptation. This has direct implications for transnational expansion strategies: market entry requires not just product localisation, but commercial model adaptation aligned with the target environment's buyer structure, evidence requirements, and funding dynamics. From a methodological standpoint, the composite index introduced in this study advances the evidence base underpinning the Figure 1 ratings from a structured rubric to a fully reproducible scoring procedure. By grounding each country–factor score in three to five verified sub-indicators classified according to the GRADE framework, normalised by the min–max method, and aggregated using AHP-derived weights, the index provides a transparent and replicable alternative to expert-assigned scores. Monte Carlo sensitivity analysis confirmed the robustness of all four factor rankings across the three countries under ±20% weight perturbation, supporting the stability of the reported comparisons.

Recommendations

Recommendations for Policymakers

Policymakers should focus on developing transnational innovation corridors that connect Ukrainian technical talent with UK clinical validation infrastructure and US scaling capabilities. These corridors would benefit from streamlined regulatory pathways, coordinated funding mechanisms, and robust knowledge exchange programs that facilitate collaboration across borders. In parallel, the creation of specialised regulatory sandboxes for AI health technologies is essential to balance innovation acceleration with appropriate safeguards, offering startups access to representative healthcare data, clinical validation pathways, and targeted regulatory guidance.

Investment in specialised education programs should be prioritised to build the necessary talent pipeline. These multidisciplinary programs should combine clinical, technical, and entrepreneurial training to create a workforce specifically prepared for AI health innovation challenges, addressing the current skills gap that exists in all three ecosystems.

Recommendations for Startup Founders

Healthcare remains a high-trust domain where adoption depends fundamentally on stakeholder confidence, regardless of national context. Startup founders should therefore invest significantly in evidence generation, stakeholder engagement, and transparency initiatives that build trust among clinicians, patients, and payers. This trust-building should be accompanied by adaptive market entry strategies that can flexibly respond to different healthcare systems' requirements rather than attempting to force solutions designed for one system into incompatible environments.

Future Research

Future research should investigate companies that successfully operate across multiple innovation ecosystems to identify optimal organisational structures and knowledge transfer mechanisms. Such studies would provide valuable insights into effective models for transnational innovation in AI health technologies and could guide both policy and investment decisions. This cross-border research should be complemented by comparative studies of AI health technology adoption across different healthcare systems to identify facilitators and barriers in each context, helping to develop more effective implementation strategies.

References

Alan Turing Institute. (2024). *Our strategy*. The Alan Turing Institute. https://www.turing.ac.uk/about-us/our-strategy

Attitudes to AI. (2025). *How do people feel about AI?* Ada Lovelace Institute and The Alan Turing Institute. https://attitudestoai.uk

Autio, E., Nambisan, S., Thomas, L. D. W., & Wright, M. (2018). Digital affordances, spatial affordances, and the genesis of entrepreneurial ecosystems. *Strategic Entrepreneurship Journal*, *12*(1), 72–95. https://doi.org/10.1002/sej.1266

Bessemer Venture Partners. (2024). *State of health tech 2024*. Bessemer Venture Partners. https://www.bvp.com/atlas/state-of-health-tech-2024

Bessemer Venture Partners. (2026). *State of health AI 2026*. Bessemer Venture Partners. https://www.bvp.com/atlas/state-of-health-ai-2026

Castonguay, A., Wagner, G., Motulsky, A., & Paré, G. (2024). AI maturity in health care: An overview of 10 OECD countries. *Health Policy*, *140*, 104938. https://doi.org/10.1016/j.healthpol.2023.104938

Commonwealth Fund. (2023). *U.S. health care from a global perspective, 2022*. The Commonwealth Fund. https://purl.org/scimeta/340.1

Council of Economic Advisers. (2025). *AI talent report*. The White House. https://purl.org/scimeta/340.2

Deloitte. (2023). *Global health care outlook*. Deloitte Global. https://studylib.net/doc/27683718

Department for Science, Innovation and Technology. (2024). *AI sector study 2023*. Government Digital Service. https://purl.org/scimeta/340.3

Digital Health London. (2024). *Transforming health and care through digital innovation*. Digital Health London. https://digitalhealth.london

FM Global. (2023). *FM Global resilience index: Annual methodology and results report*. FMIC. https://www.fm.com/resources/resilience-index

Fybish, A. (2024). *Top Ukrainian startups to watch in 2024*. Startup Stash. https://startupstash.com/ukrainian-startups

Glover, W. J., Crocker, A., & Brush, C. G. (2024). Healthcare entrepreneurship: An integrative framework for future research. *Journal of Business Venturing Insights*, *22*, e00476. https://doi.org/10.1016/j.jbvi.2024.e00476

Greenhalgh, T., Wherton, J., Papoutsi, C., Lynch, J., Hughes, G., A'Court, C., Hinder, S., Fahy, N., Procter, R., & Shaw, S. (2017). Beyond Adoption: A New Framework for Theorizing and Evaluating Nonadoption, Abandonment, and Challenges to the Scale-Up, Spread, and Sustainability of Health and Care Technologies. *Journal of Medical Internet Research, 19*(11), e367. https://doi.org/10.2196/jmir.8775

Guyatt, G., Oxman, A. D., Akl, E. A., Kunz, R., Vist, G., Brozek, J., Norris, S., Falck-Ytter, Y., Glasziou, P., DeBeer, H., Jaeschke, R., Rind, D., Meerpohl, J., Dahm, P., & Schünemann, H. J. (2011). GRADE guidelines: 1. Introduction – GRADE evidence profiles and summary of findings tables. *Journal of Clinical Epidemiology*, *64*(4), 383–394. https://doi.org/10.1016/j.jclinepi.2010.04.026

Health Foundation. (2025). *AI in the NHS 2025*. The Health Foundation. https://www.health.org.uk/events/ai-in-the-nhs-2025

Health Innovation Network. (2019). *HealthTech landscape overview: Making sense of the MedTech innovation maze*. The AHSN Network. https://purl.org/scimeta/340.5

Health Innovation Network. (2024). *Case studies in healthcare innovation*. Health Innovation Network. https://thehealthinnovationnetwork.co.uk/case_studies

HIMSS. (2023). *Electronic medical record adoption model (EMRAM): The global standard for EMR transformation*. Healthcare Information and Management Systems Society. https://www.himss.org/maturity-models/emram

Huma. (2024). *Huma platform: A fully integrated suite of AI and digital health products*. Huma. https://www.huma.com

IT Ukraine Association. (2024). *Digital tiger: The market power of Ukrainian IT for 2024*. IT Ukraine Association. https://itukraine.org.ua/files/DigitalTiger2024.pdf

King's Fund. (2025). *Key facts and figures about the NHS*. The King's Fund. https://purl.org/scimeta/340.6

Knowles, M., & Somaiya, M. (2024). *2023 year-end digital health funding: Break on through to the other side*. RockHealth. https://purl.org/scimeta/340.12

Lawrence, C. (2026). *Why Ukraine is becoming a global healthtech frontier*. Tech.eu. https://purl.org/scimeta/340.17

Lee, J., Suh, T., Roy, D., & Baucus, M. (2019). Emerging technology and business model innovation: The case of artificial intelligence. *Journal of Open Innovation: Technology, Market, and Complexity*, *5*(3), 44. https://doi.org/10.3390/joitmc5030044

Li, Y., Zhang, J., Gu, Y., Zhu, Y., He, Q., & Li, L. (2019). Comparative Study on Global Development Strategies of Artificial Intelligence in Healthcare. *Chinese Journal of Engineering Science, 21*(6), 106. https://doi.org/10.15302/j-sscae-2019.10.003

Malakhov, K. S. (2023). Insight into the Digital Health System of Ukraine (eHealth): Trends, Definitions, Standards, and Legislative Revisions. *International Journal of Telerehabilitation, 15*(2). https://doi.org/10.5195/ijt.2023.6599

Marjanovic, S., Marciniak-Nuqui, Z., Toole, H., Stockwell, S., Parkinson, S., Bucseneanu, S., Grant, J., & Fahy, N. (2025). *From research to reality: Research and innovation in the NHS as key to enabling the 10-Year Plan* (Report No. RR-A3808-1). RAND Corporation. https://purl.org/scimeta/340.7

National Academy of Medicine. (2022). *Sharing health data: The Why, the Will, and the Way Forward*. National Academy of Sciences. https://purl.org/scimeta/340.8

NHS England. (2019). *NHS long term plan*. NHS UK. https://www.longtermplan.nhs.uk

NHS England. (2024). *AI knowledge repository*. NHS England. https://digital.nhs.uk/services/ai-knowledge-repository

NICE. (2022). *Evidence standards framework for digital health technologies*. NICE. https://purl.org/scimeta/340.9

NVCA. (2025). *NVCA Releases 2025 Yearbook Showcasing 2024 VC Trends*. National Venture Capital Associations. https://purl.org/scimeta/340.10

OECD. (2020). *Handbook on constructing composite indicators: Methodology and user guide*. OECD. https://doi.org/10.1787/9789264043466-en

OECD. (2023). *Health at a Glance 2023: OECD indicators*. Organisation for Economic Co-operation and Development. https://doi.org/10.1787/7a7afb35-en

Ookla. (2024). *Speedtest global index: Fixed broadband performance by country (Q4 2024)*. Ookla, LLC. https://www.speedtest.net/global-index

Oxford Insights. (2022). *Understanding UK AI R&D commercialisation and the role of standards: Understanding UK AI R&D commercialisation and the role of standards*. Department for Science, Innovation and Technology. https://purl.org/scimeta/340.11

Porter, M. E. (1990). The competitive advantage of nations. *Harvard Business Review*, *68*(2), 73–93. https://hbr.org/1990/03/the-competitive-advantage-of-nations

Portulans Institute. (2023). *Network readiness index 2023: Digital transformation in the post-pandemic era*. Portulans Institute. https://networkreadinessindex.org

Saaty, T. L. (1980). *The analytic hierarchy process: Planning, priority setting, resource allocation*. McGraw-Hill. https://books.google.com/?id=Xxi7AAAAIAAJ

SaiLab Finland. (2024). *Miltton – Healthcare in Ukraine*. Sailab – MedTech Finland. https://purl.org/scimeta/340.13

Silicon Valley Bank. (2024). *Healthcare industry trends: 2024 annual report*. First-Citizens Bank & Trust Company. https://purl.org/scimeta/340.14

Spigel, B. (2017). The relational organization of entrepreneurial ecosystems. *Entrepreneurship Theory and Practice*, *41*(1), 49–72. https://doi.org/10.1111/etap.12167

St. Louis, D. (2024). *Digital health adoption is surging, but so is consumer distrust*. Strategic Communications Group. https://purl.org/scimeta/340.4

Stanford Human-Centered AI Institute. (2024). *AI index report 2024*. Stanford University. https://aiindex.stanford.edu/report

Startup Genome. (2023). *Adaptation and resilience: First-hand insights into the Ukrainian startup ecosystem*. Startup Genome. https://purl.org/scimeta/340.15

Startup Genome. (2024). *Global startup ecosystem report 2024*. Startup Genome. https://startupgenome.com/reports/gser2024

Statista. (2024). *Medical technology – Ukraine*. Statista GmbH. https://www.statista.com/outlook/hmo/medical-technology/ukraine

Tech Nation. (2024). *The Tech Nation Report 2024 UK Tech in the Age of AI*. Angel Capital Scotland. https://purl.org/scimeta/340.16

The Week. (2023). *Babylon Health: The failed AI wonder app that 'dazzled' politicians*. The Week. https://purl.org/scimeta/340.18

United Nations Development Programme. (2023). *Human development report 2023/24*. UNDP. https://hdr.undp.org/content/human-development-report-2023-24

World Bank. (2023). *World development indicators: Research and development expenditure (% of GDP)*. World Bank Group. https://purl.org/scimeta/340.19

World Health Organization. (2023). *The Global Health Observatory*. World Health Organization. https://www.who.int/data/gho

Ziakis, C., Vlachopoulou, M., & Petridis, K. (2022). Start-Up Ecosystem (StUpEco): A Conceptual Framework and Empirical Research. *Journal of Open Innovation: Technology, Market, and Complexity, 8*(1), 35. https://doi.org/10.3390/joitmc8010035