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Digitalisation of International Trade in Intellectual Properties: An Approach Based on the Utility Theory of Technology Value

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ABSTRACT

In the era of globalisation and digital transformation, international trade has expanded beyond traditional goods and services to include the exchange of intellectual properties (IPs), particularly technology. As intangible assets become key drivers of global economic growth, accurately valuing them remains a complex challenge due to their inherent creativity, complexity and uncertainty. This study proposes a novel framework grounded in utility theory to assess technology value within the context of international IP trade. By integrating the utility theory of value and the literature on technology and venture investment into a cohesive model, the framework captures four key attributes of technology value: utility size, quality, delivery and risk. To operationalise this framework, we introduce a valuation method that leverages artificial intelligence (AI) and big data analytics. This AI-powered approach enhances the objectivity, efficiency, affordability and scalability of technology valuation, enabling more transparent, data-driven IP trade globally.

1 | Introduction

In recent decades, the globalisation of production has expanded the scope of international trade from the exchange of goods and services to the trade of knowledge (Baldwin and Evenett 2015), particularly in intellectual properties (IPs) such as patented technologies, trademarks, copyrights, brands, software and data. This shift has been facilitated by global value chains (GVCs) and foreign direct investment (FDI) activities (Fu and Ghauri (2021); Xing et al. 2021). On average, these IPs contribute one-third of the total value of products—nearly double the share of tangibles, which are predominantly produced in the developing world (WIPO (World Intellectual Property Organization) 2017). The contribution of IPs to the value-added in high-tech products is even greater, underscoring the importance of cross-border IP trade in stimulating global economic development.

Despite the growing significance of intangible assets in trade, FDI and global economic growth, existing literature has not fully explored international trade in these assets, primarily focusing on the value of goods and services crossing physical borders (Xing et al. 2021). In particular, the tacit and complex nature of technology, coupled with market uncertainties, creates knowledge asymmetries between inventors and investors. This hinders the development, transfer and commercialisation of technology for large-scale use in the economy and society (Hagelin 2002; Haskel and Westlake 2018). Thus, accurate valuation of technology assets is critical for facilitating international trade in IPs.

While Fu and Ghauri (2021) have provided a framework for identifying different types of intangible assets, a significant challenge remains in effectively and accurately measuring the value of intangibles, particularly technology. Although the literature has discussed the impact of individual factors on the value of technologies (e.g., Harhoff et al. 1999; Reitzig 2003; Hall and MacGarvie 2010; Moser et al. 2018), and various valuation approaches have been developed in finance (e.g., Mard 2000; Thorn et al. 2011; Oriani and Sobrero 2008; Vega-González et al. 2010; Baek et al. 2007; Hsu et al. 2021; Macmillan et al. 1985; Warnick et al. 2018), there is still a lack of a comprehensive framework for technology valuation. Furthermore, no suitable valuation tool exists to bridge the gap between abstract theories and practical applications.

Existing theories of value—such as the labour theory of value (Marx 1867; Schroeder 2008), the cost theory of value (Sraffa 1951; Kurz 2000) and the utility theory of value (Menger 1976)—provide a valuable theoretical foundation for defining and explaining the value of tangible goods, particularly labour-intensive products. However, these theories have significant limitations when applied to the valuation of technology, which is characterised by high levels of human creativity, technical complexity, intangibility and substantial risks and uncertainties in realising its potential.

Moreover, the evolution of digital technologies has reshaped modern business operations and communication practices. As highlighted by the World Trade Organization (WTO) in (2023), digital transformation has revolutionised how enterprises function internally and interact with stakeholders, leading to a remarkable surge in the global trade of IPs facilitated through computer networks and digital intermediary platforms. These platforms serve as virtual marketplaces where ideas, innovations and creative works can be exchanged and commercialised across geographical boundaries with unprecedented ease. By leveraging digital networks and intermediaries, businesses can now engage in the cross-border trade of IPs more efficiently, securely and cost-effectively than ever before.

Digitalisation can address significant challenges in valuing technologies, particularly regarding data availability and comparability, which complicates the determination of accurate monetary values. The traditional valuation process may take weeks to months (J.P. Morgan 2024; Patel 2024). However, recent advancements in digital technologies, such as artificial intelligence (AI), cloud services and big data analytics, have the potential to enhance data collection and enable the development of more effective and precise valuation methods.

This study aims to investigate the digitalisation of international trade in IPs by introducing a comprehensive framework that synthesises existing literature on value determination and systematically integrates key factors in the technology evaluation process. Additionally, it seeks to develop a technology evaluation method that bridges the gap between theory and practice, leveraging digital tools. The study uses an example of startup firms in the information and communication technology (ICT) sector as initial empirical evidence to validate the framework and illustrate the potential for developing an objective estimation methodology based on big data. Further examples are presented to demonstrate how the framework facilitates international IP trade.

This research makes a significant contribution to the existing literature by introducing a novel framework rooted in utility theory within the context of knowledge production. This framework departs from traditional valuation approaches by considering the distinct characteristics of knowledge-intensive technologies that impact overall utility and its evolving delivery to society, encompassing both users and non-users.

In contrast to conventional valuation techniques, this framework emphasises the multidimensional attributes that shape the intrinsic value of technology: the nature and scale of its utility, the quality of this utility, its mode of delivery and the associated risks and sustainability. Notably, this framework extends beyond a mere focus on technology-related features by considering additional factors such as the technology's life cycle stage, the maturity of supporting infrastructure, relevant institutional frameworks, complementary technologies and team dynamics. In other words, this novel framework synthesises existing concepts (e.g., utility theory of value and the literature on technology and venture investment) into a cohesive model.

This study also bridges the gap between abstract theories and practical applications, employing digital tools like big data analytics and AI algorithms for technology value prediction. Specifically, it introduces an AI-enhanced model that automates the entire valuation process, enabling swift and impartial estimation of technology values in practice. By overcoming existing obstacles in technology transfer and trade, this model enhances the objectivity, accessibility, accuracy, affordability and efficacy of global IP trade, thereby fostering the digitalisation of trade in knowledge-intensive assets and IPs worldwide.

Furthermore, this paper lays the groundwork for the future development of an empirical estimation methodology that integrates digital tools, catering to the practical needs of investors, innovators and intermediaries. Equipped with digital capabilities, this method holds promise for application in real-world scenarios and could also generate aggregated trade statistics, offering valuable insights for decision-makers and stakeholders in the realm of global IP trade.

Overall, this research advances our understanding of technology valuation within the digital economy and paves the way for practical applications that could revolutionise how technology assets are evaluated, traded and leveraged in the global marketplace, ultimately contributing to the digitalisation and optimisation of trade in knowledge-intensive assets and intellectual properties on a global scale.

The structure of this paper is as follows: Section 2 details the literature review. Section 3 proposes the utility theory of technology value. Section 4 develops the AI-empowered technology valuation model and presents implications for the digitalisation of cross-border IP trade, and Section 5 concludes.

2 | The Literature

2.1 | Economic Literature on Value

The economic literature on value can be categorised into three main streams. Both the labour theory of value (Marx 1867; Rubin 1978; Schroeder 2008) and the cost-of-production theory of value (Araujo 2019; Kurz 2000; Sraffa 1951) effectively explain the value of labour-intensive products. However, they fall short of capturing the value of technologies that stem from human creativity. Given the same number of work hours and capital inputs, individuals with varying levels of creativity can produce significantly different ideas and technologies.

The third stream—utility theory of value—defines price and value based on the degree of 'use' an individual derives from a commodity (Menger 1976). This theory rests on the assumption that individuals have preferences for different outcomes, making it widely utilised in microeconomics to analyse behaviour and decision-making. It posits that the unit price of a product is determined by its marginal utility. However, utility value has been criticised for its subjectivity, as both preferences and assigned values are inherently personal (Gordon 1964; Jevons 1866). Some literature also defines value as the worth of goods or services as determined by markets (Beckert and Aspers 2011; Schroeder 2008), yet it is often the market that determines price rather than intrinsic value.

Empirical studies have provided valuable insights into patent value indicators, such as the number of forward citations, backward references and claims (Trajtenberg 1990; Harhoff et al. 1999; Reitzig 2003; Hall and MacGarvie 2010; van Zeebroeck and van Pottelsberghe de la Potterie 2011; Moser et al. 2018). However, patent statistics represent only one aspect of the monetary value of technologies. The value of patents has also been estimated using patent renewal data (Schankerman and Pakes 1986), benefits from successful opposition (Reitzig 2004) and the incremental rents earned by patents (Arora et al. 2008). These estimates, however, often provide insights into only part of a technology's value (Bessen 2008) or focus solely on the value of patent protection rather than the technology itself. For example, Arora et al. (2008) found that renewal value tends to underestimate patent value, as it overlooks the strategic role of exclusion rights in the context of cumulative or complementary inventions.

2.2 | Innovation and Finance Literature on Technology Valuation

Prior research in innovation and finance has focused on various methods employed in practice for technology valuation. These include quantitative methods such as the cost approach (Mard 2000), the income approach (Thorn et al. 2011), real option analysis (Eichner et al. 2007; Oriani and Sobrero 2008) and structural models (Park and Park 2004), as well as qualitative approaches including fuzzy multiple criteria comparison (Cheng 2013), the specific value points approach (Vega-González et al. 2010) and peer benchmarking (Baek et al. 2007; Hsu et al. 2021). Hybrid approaches have also been proposed (Doerr et al. 2006). However, these methods have certain drawbacks and limitations. For instance, the cost model quantifies current costs to estimate the economic value of technology, but costs do not necessarily equate to future benefits, particularly for creativity-intensive technologies. The income-based method, real option approach and hybrid methods rely on predictions of future income, which are inherently uncertain. The benchmarking approach assumes that potential buyers would pay similar prices for comparable technologies (Reilly and Schweihs 1999); however, finding such comparable technologies and their transaction prices is often challenging due to a lack of transparency (Baek et al. 2007).

Additionally, Macmillan et al. (1985) conducted a pioneering study that employed an integrated framework to examine the criteria used by venture capitalists (VCs) when evaluating new venture proposals. By surveying 100 VCs, they analysed the significance of factors such as the entrepreneur's personality, experience, product characteristics, market characteristics and financial considerations. Their results indicated that the quality of the entrepreneur was the most crucial factor in funding decisions. Subsequent studies have highlighted other attributes of entrepreneurs, such as passion and openness to feedback, as important in VC investment decisions (Warnick et al. 2018). Several teaching cases have also explored how VCs evaluate potential ventures (Roberts and Barley 2004).

Recent studies have developed new methods to capture additional patent-related information about technologies. Kogan et al. (2017) based their valuations on stock market reactions following the announcement of patent grants. Bellstam et al. (2021) and Arts et al. (2021) argue that text analysis can provide more accurate insights than patent statistics in capturing technological novelty. Furthermore, studies by Montani et al. (2020) and Blank (2020) have identified several critical aspects generally absent from the aforementioned valuation approaches, such as the need for further forecasts and the importance of addressing specific business models. However, while these studies offer interesting insights, they do not provide a systematic framework for the factors deemed important in the evaluation process, nor do they yield comprehensive estimates of the value of technology.

3 | A Utility Theory of Technology Value

3.1 | Utility of Knowledge-Intensive Technology

In economics, utility refers to the total satisfaction or benefits derived from consuming a good or service, which is typically labour- or capital-intensive. Figure 1 illustrates the total utility and marginal utility for individual consumers (a) and society as a whole (b) (Stigler 1950). For knowledge-intensive products such as technology, the dynamics of consumer utility unfold differently. For most new technologies, the total utility derived from initial use can increase dramatically after the first experience, as shown by the steeper slope of the total utility curve in the initial phase (Figure 2a). This slope varies significantly across different technologies. For instance, with streaming services for movies, shows or music, increased usage correlates with higher total utility. However, the rate of utility growth gradually slows as additional use yields diminishing satisfaction. Conversely, in cases like vaccines, the first dose provides most of the utility needed, making any subsequent doses redundant unless a booster is required due to waning immunity. For technologies embedded in durable products, such as smartphones and laptops, total utility is linked to the duration of use rather than the number of units purchased. This utility can be further enhanced by

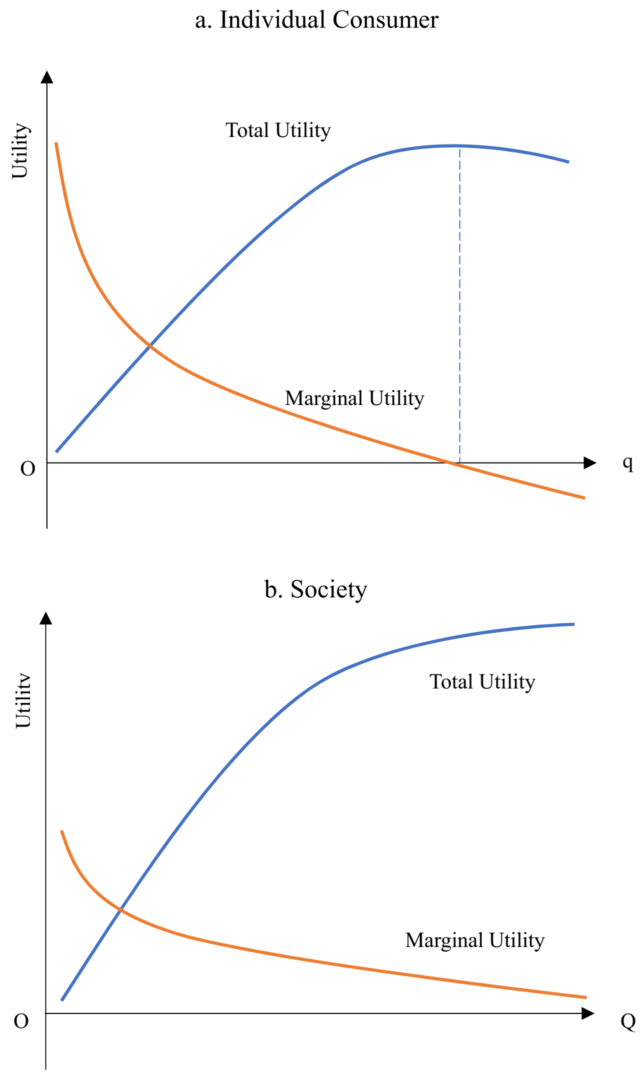

FIGURE 1 | Utility of traditional labour- or capital-intensive good or service. For traditional labour- or capital-intensive goods or services, total utility increases at a decreasing rate, resulting in a concave shape. Simultaneously, the marginal utility derived from consuming an additional unit of a good declines as consumption increases, applicable to both individual consumers (a) and society as a whole (b). [Colour figure can be viewed at wileyonlinelibrary.com]

complementary technologies like Wi-Fi, updated software and additional app installations.

Unlike labour- or capital-intensive goods, the marginal cost of independently replicating technology can be negligible or even zero after its invention, despite the substantial fixed costs associated with development and patenting, such as research and development (R&D), design and legal fees. Even when technology is tied to physical goods or services (e.g., pharmaceuticals, medical devices or fintech solutions) or when licences apply to patented technology, the marginal cost for each additional product or licence can be very low due to economies of scale.

The shapes of total utility and marginal utility, along with the low or negligible marginal cost of technology, indicate that traditional valuation theories are inadequate for explaining the value

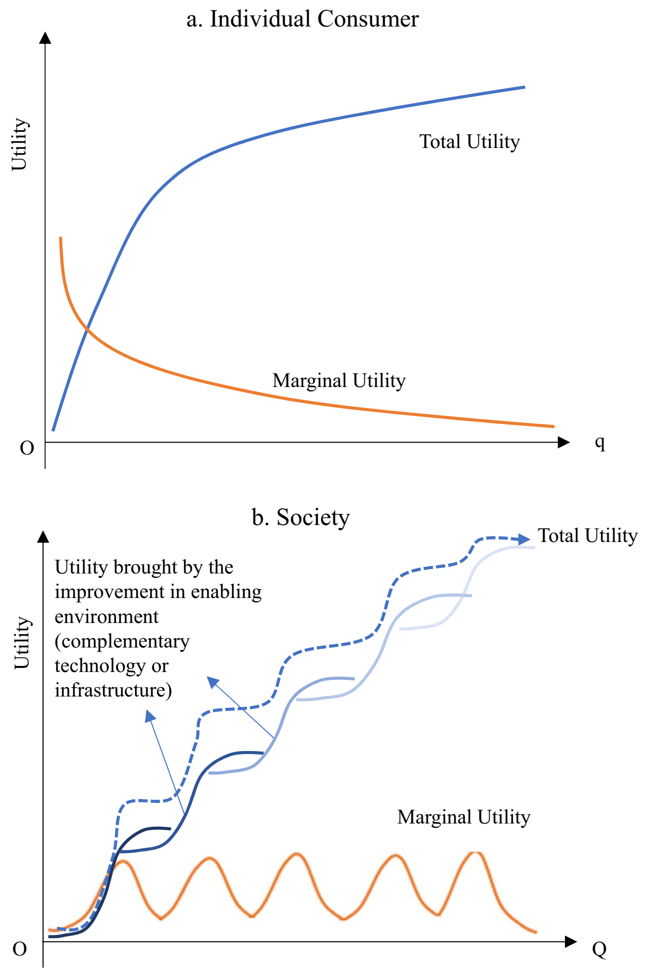

FIGURE 2 | Utility of new knowledge-intensive technology. For emerging knowledge-intensive technologies, the total utility that individual consumers derive can increase dramatically after initial use. However, this growth in utility typically slows down over time, as continued use beyond a certain point yields diminishing returns in user satisfaction. Once a technology has been invented, the marginal cost of reproducing or replicating it independently can become negligible or even reach zero. From a broader societal perspective, the total utility of a technology may follow a series of utility S-curves, which capture the successive waves of adoption and value creation as new complementary technologies emerge, infrastructure improves or more users engage with the innovation at varying stages. In this context, the total utility of the society forms a stair-step trajectory over time, as illustrated by the dotted blue pathway, including total utility for all users as well as that of non-users (through externality, e.g., environmental impacts of clean technology). Furthermore, the marginal utility of technology for society may exhibit a sequence of bell-shaped curves, reflecting cycles of rising and falling incremental benefit as each new wave of adoption and application plateaus. [Colour figure can be viewed at wileyonlinelibrary.com]

of technology, particularly when it lacks a physical presence. Quantifying and capturing the value of technology should be based on its 'value in use'—a concept rooted in Adam Smith's idea of utility (Stigler 1950). For example, the value of patented medical technology should not be determined solely by its production costs (capital and labour) but rather by the life-saving benefits it provides.

Measuring the value in use of technology is complex due to several specific characteristics. First, knowledge-intensive technology involves high levels of human creativity and technical complexity, in addition to labour and capital. Second, technologies carry greater risks and uncertainties when realising their full potential. Third, consumers' risk sensitivity and usage of technology evolve over time, as illustrated by Rogers' bell-shaped technology adoption curve, which features early adopters, the majority and laggards (Rogers 1995). Fourth, certain technologies, such as the internet and social media platforms, exhibit network effects, where a consumer's utility increases as the number of users grows (Church and Gandal 1992). Fifth, many technologies generate positive externalities, such as the environmental benefits of clean energy technologies, enhancing societal utility beyond that of individual users. Finally, the utility of new technology is dynamic and can be improved by advancements in the enabling environment, such as the introduction of complementary technologies or the development of infrastructure that enhances functionality, efficiency or user experience. For instance, the utility of electric vehicles (EVs) has increased due to the widespread installation of charging stations and advancements in battery technology.

Considering these intrinsic characteristics and building upon the utility theory of value (Stigler 1950), the utility of technology should encompass the benefits it provides to both consumers and society at large. The total utility of new technology for society (as shown in Figure 2b) typically starts slowly, reflecting early adoption with high risk, then rises rapidly as a critical mass is reached or network effects are achieved, and finally flattens out as utility approaches saturation or diminishing returns (a single S-curve). For certain technologies, such as solar panels, the initial utility may be confined to direct users, but as adoption grows, the reduced emissions benefit non-users as well. Consequently, the total utility curve may exhibit a convex shape in the early stages, reflecting societal benefits that exceed aggregated individual utility. Furthermore, when a new complementary technology emerges or new infrastructure becomes available, an additional S-shaped utility curve (representing new benefits) is created for adopters of the complementary technology or users of the new infrastructure, while those who do not benefit from this new utility remain on their original S-curve. Over time, multiple utility S-curves may be generated, leading to a total utility for all users that combines these curves into a stair-step progression, as illustrated by the dotted blue pathway in Figure 2b.

Unlike the decreasing marginal utility curve typical of labour- and capital-intensive goods, the marginal utility of technology for society may follow a sequence of bell-shaped curves. It starts low during the early adoption phase, increases as the technology gains wider acceptance—driven by positive externalities and network effects—and then tapers off as total utility approaches its peak. This bell-shaped curve may repeat with successive waves of improvement in the enabling environment.

3.2 | Utility-Based Technology Valuation Framework

The value of technology is determined by its utility for both users and non-users across society, influenced by the enabling environment and the stages of adoption, each entailing varying levels of risk and uncertainty. Building on the utility theory of value (Marx 1867; Hicks and Allen 1934), this study develops a comprehensive framework for technology valuation (Figure 3) that considers four key factors: (1) the nature and size of the utility; (2) the quality of the utility; (3) the delivery of the utility and (4) the risk and sustainability of the utility.

3.2.1 | Nature and Size of the Utility

The economic utility of a technology for society is directly influenced by its nature and the number of users. Dimensions of the technology's nature—such as the format of protection (e.g., patent, copyright, open-source licensing), sectoral application and functionality—affect market demand, a crucial factor in determining the value of patented technology (Kalcheva et al. 2018). A larger market size presents better opportunities for future profits and the potential to address a broader range of needs (Dubois et al. 2015). Only technologies that meet market demands and for which consumers are willing to pay can be deemed valuable (Vega-González et al. 2010).

3.2.2 | Quality of the Utility

The quality of a technology's utility refers to its effectiveness in fulfilling its intended purpose and enhancing user experience and satisfaction. Key attributes such as novelty, scarcity, reliability, the strength of the innovation team and the technology's position in its life cycle are vital in determining its usefulness to users.

3.2.2.1 | Novelty, Scarcity and Reliability of the Technology. Novelty, scarcity and reliability are crucial for fulfilling user needs and creating new ones (Bessen 2008; Fischer and Leidinger 2014). Novelty describes the technological distance between the invention and prior art (Reitzig 2003). From a utility perspective, consumers derive greater satisfaction from differentiated technologies. Scarcity relates to the limited availability of technology, providing it with a competitive edge and granting the owner monopoly power and barriers to entry. Breakthrough technologies can offer unique competitive advantages and significant revenue to the inventing organisation (Achilladelis et al. 1990). Reliability refers to the technology's ability to consistently perform according to specifications, making it a key consideration during production, marketing and usage.

3.2.2.2 | R&D Team and Entrepreneur Characteristics. Novelty is closely linked to the creativity and quality of R&D teams, as well as the characteristics of entrepreneurs. Team characteristics can influence opportunities (e.g., access to information, resources, technology and productivity) and constraints (e.g., regulatory hurdles, restrictions on capital or information) encountered during the innovation and commercialisation process (Damanpour and Schneider 2006). The quality of the R&D team directly affects the rate of innovation, the effective use of technology and the overall utility it provides. Teams with a learning-rich production system can enhance technological dynamism, improving access to resources,

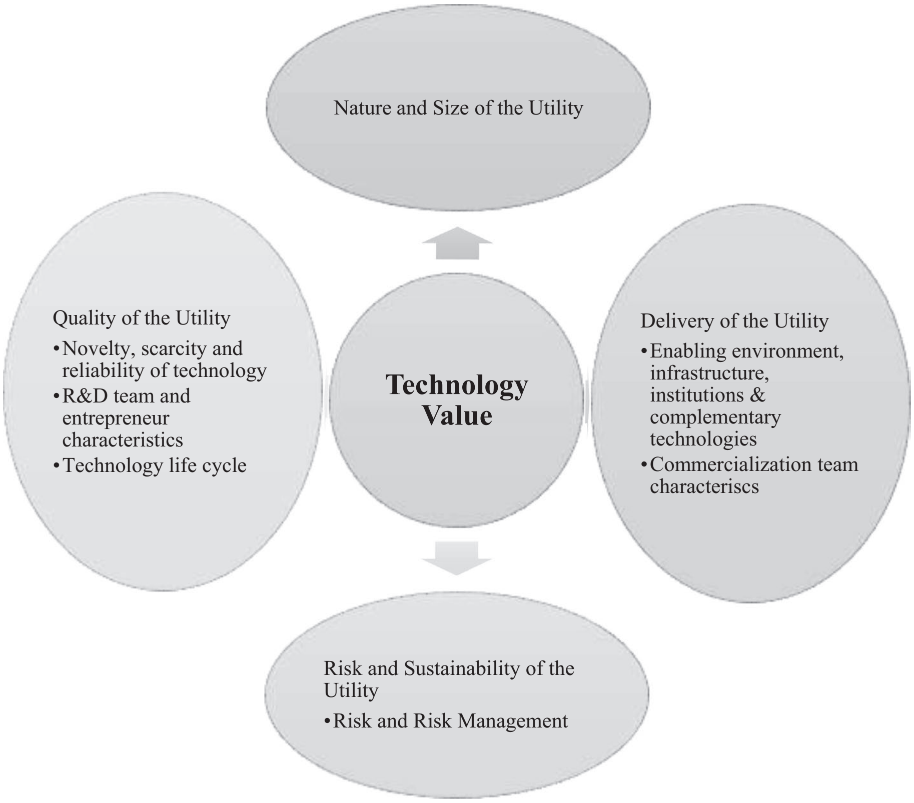

FIGURE 3 | Valuation framework of technology based on utility theory.

technological information, complementary technologies and knowledge hubs (Fennell 1984). Similarly, entrepreneurial leadership and organisational features affect a firm's capability to innovate and fully realise the potential utility of its technology (Boone et al. 2019).

3.2.2.3 | Position in the Technology Life Cycle. The novelty and reliability of a technology are also influenced by its current stage in the technology life cycle (Taylor and Taylor 2012). The commercial potential and perceived value of a technology typically follow a four-phase cycle: introduction, growth, maturity and saturation (Tipping et al. 1995). This cycle has been observed across multiple industries, such as chemicals (Achilladelis et al. 1990) and ICT (Nieto et al. 1998). The life cycle reflects shifts in individual utility, market size and technological evolution over time.

In the early research and introduction phase, the technology's value is generally low and increases slowly as radical innovations emerge. The growth phase leads to increased individual and societal utility, a larger market size and the generation of positive externalities and network effects. During the maturity stage, societal marginal gains from the innovation tend to diminish, and the market stabilises, signalling slower growth in total utility. In the final saturation phase, incremental innovations yield diminishing returns, overall utility flattens and commercial value declines unless radical innovations occur in complementary technologies.

3.2.3 | Delivery of the Utility

The utility of technology cannot be delivered to users without an enabling environment and a capable commercialisation team. This includes the presence of complementary technologies, infrastructure, institutional conditions and the capabilities of the commercialisation team.

3.2.3.1 | Enabling Environment. The enabling environment encompasses the readiness of infrastructure, institutional frameworks and complementary technologies. Few technological products function in isolation; rather, technological infrastructure promotes both the innovation process and the effective use of technology (Blind and Grupp 1999). Many technologies depend on a network of physical and digital infrastructure to operate effectively.

The institutional environment is essential for delivering the utility of certain technologies, particularly in sectors like healthcare, finance and transportation, as well as in emerging areas like AI. It ensures safety, ethics, security and compliance, enabling broader adoption of technology. Strong IP protection plays a pivotal role in incentivising innovation (Fagerberg and Srholec 2008; Furman et al. 2002) and ensuring the utility derived from new technologies, especially in industries like pharmaceuticals.

Complementary technologies enhance a technology's feasibility and overall utility, enabling greater value for end users (Nambisan 2002). However, few studies adequately integrate the influence of complementary technologies into the valuation framework (e.g., Chang et al. 2005). These complementary technologies may take the form of component parts or production methods. Consequently, a firm's technology may possess commercial value only when it is supported by technologies from other firms. The impact of complementary technologies is not limited to cost avoidance for developing complementary products; it also encompasses the potential for earlier market introduction and profit realisation. Their presence can expedite the expansion of the initial market and accelerate product growth (van de Ven 1986).

3.2.3.2 | Commercialisation Team Characteristics. The characteristics of the commercialisation team are crucial for delivering a technology's utility to users (Dhewanto and Sohal 2015). This team is responsible for successfully bringing a new technology to market, ensuring it is not only developed but also effectively introduced to users. They must possess strategic marketing skills and strong communication abilities with various stakeholders. Therefore, the characteristics of a firm's commercialisation team play a vital role in shaping the technology's diffusion path, usage, societal utility and value creation.

3.2.4 | Risk and Sustainability of the Utility

The risk and sustainability of a technology's utility are vital for its sustainability and value, as they influence long-term viability and growth in a dynamic environment. These factors determine whether a technology will yield sustained benefits for consumers and society, delivering increasing returns for firms over time. Risks are inherent in the innovation process and in translating outcomes into commercially viable products or processes that can be successfully scaled. High levels of risk can adversely impact both the realisation and maintenance of a technology's utility (Gans et al. 2008). Conversely, technologies with significant future potential—despite associated uncertainties—are often pivotal in fostering further innovation. Such technologies tend to be adaptable, supporting the development of complementary inventions, additional functionalities and access to new markets. This adaptability helps sustain and enhance their utility and overall value over time.

4 | Application of the Utility Theory of Technology Value

4.1 | Potential Indicators and Data Sources

Our framework can be applied and validated by estimating the following model:

$$Y_{it} = f(X) + \varepsilon \tag{1}$$

where Y refers to the monetary value of technology for firm i at time t, and X represents a set of factors capturing the four attributes associated with the utility of the technology, and ε denotes idiosyncratic errors.[1] Table 1 presents potential indicators and data sources used in this modelling approach.

In practice, technology value can be proxied using a variety of indicators. These include the actual sale prices, licensing fees, technology acquisition costs through mergers and acquisitions (M&As), expected future sales or the amount of funding received—particularly in early-stage ventures—which serves as a proxy for expected returns (Fischer and Leidinger 2014).[2] These data could be sourced from financial datasets such as Bloomberg, Compustat, Refinitiv, CB Insights, firm-level annual reports and financial statements, and venture capital datasets in different countries. Actual technology transaction information can be obtained from private databases maintained by technology marketplaces or patent exchanges.

The nature and size of a technology's utility can be inferred from its function, IP protection format and potential market size. These characteristics may vary significantly by industry. For example, the pharmaceutical sector heavily depends on patented drugs and strict regulatory approvals to access various markets, whereas software technologies may involve a combination of patents, copyrights, trade secrets or open-source licences. Market size plays a crucial role in shaping the initial roadmaps and planning processes (McCarthy 2003), with larger markets often enhancing the total realisable value of a given technology (Acemoglu and Linn 2004). Potential market size can be measured through the total revenue generated by similar technologies in the sector, the estimated number of potential users (e.g., disease prevalence for pharmaceuticals or user adoption rates for software) and competitor market shares.

To assess the quality and novelty of technology, a range of indicators can be employed. For patented technologies, key indicators include the number of claims, forward citations to the patent, backward citations in the patent application, patent family size and the number of distinct four-digit International Patent Classifications (IPC) classes of the patent (Lanjouw and Schankerman 2004). The number of claims reflects the scope and technical details of the invention for protection, with more claims indicating better technological performance (Tong and Frame 1994). Forward citations are widely recognised as a proxy for patent quality, measuring its contribution to prior art (Hall and MacGarvie 2010; Harhoff et al. 1999). Backward citations, including references to prior patents and scientific publications, provide insights into the existing technological foundation upon which the innovation is built (Ziedonis 2004), though their effect on technology value is ambiguous (Hall et al. 2001; van Zeebroeck 2011). A patent with a high family size means it is protected in multiple countries outside their home markets, reflecting the technological importance of innovation and market opportunities (Lanjouw and Schankerman 2004). More IPC classes indicate broader industrial applicability and novelty, and patents with wide disciplinary coverage tend to be more valuable due to greater potential market, enhanced exclusionary rights and higher barriers for competitors (van Zeebroeck and van Pottelsberghe de la Potterie 2011). These indicators can be obtained from free or paid databases of patent offices.

For non-patented technologies, indicators for quality can vary significantly depending on the type of technology and industry context. In the case of digital technologies, for instance, novelty and quality are often gauged by indicators such as licensing activity, user engagement and platform metrics such as streaming frequency, subscription levels or GitHub stars. These metrics serve as proxies for popularity, perceived usefulness, reliability and community impact. In other industries, such as green and clean technologies, the quality and novelty of non-patented technologies might be reflected in impact metrics (e.g., emission reduction and energy efficiency gains) and recognition by institutions (e.g., certifications and awards). Additionally, for

TABLE 1 | Potential indicators and data sources.

Potential indicators	
Technology value	Actual sale prices and licensing fees; Costs in M&As; Expected sales; Amount of funding received.
Nature and size of utility	Protection format (e.g., number of patents, copyrights, software, etc.); Market size metrics: revenue, output in the specific sector, number of users and potential market growth; Patent family size; Trade policy indicators, market competition and industry concentration.
Quality of the utility	
Novelty, scarcity and reliability of the technology	Patent claims, forward citations, backward citations, family size, IPC classes; Licensing activity, user engagement and platform metrics – streaming frequency, subscriptions, GitHub stars; Impact metrics, certificates and awards; Duration of IP protection, IP renewals or extensions
Position in the technology life cycle	Technology evolution indicators: trends in patent filings in specific IPC classes, publication counts in specific themes, forward citations and patent abandonment rates; User adoption metrics; Public engagement metrics: online searches, media mentions, social media trends; Market-based indicators: growth in revenue, employment and VC investment.
R&D team and entrepreneur characteristics	R&D personnel, R&D investment, key inventors' backgrounds, founders' experience and fundraising experience.
Delivery of the utility	
Enabling environment	Infrastructure and complementary technologies, e.g., road density and quality, EV charging station density, hospital beds, internet users, 5G availability, national AI adoption rates, etc. Regulatory readiness: IP protection index, regulatory quality index, stringency of environmental regulations, ease of doing business index Sector-specific regulations: number of AI bills, EV safety standards, etc. Overall business environment: market competition and concentration indices, industry clustering indicators, industrial sentiment index, entrepreneur confidence index, trade policy indicators, etc.
Commercialisation team characteristics	Employees, revenue, age, founders' previous commercialisation experience and fundraising experience.
Risk and sustainability of the utility	Employees, revenue, age, Inventors and founders' characteristics and relevant experience and track records and IP disputes; Risks related to the enabling environment.
Data sources	
Open-access databases	e.g., World Bank, WIPO, national patent offices, OECD, European Commissions, UN agencies, national government websites, national yearbooks, Google Patent, Google Scholar, Google Trends, GitHub, etc.
Commercial databases	e.g., Statista, Bloomberg, Compustat, Refinitiv, CB Insights, Yahoo Finance, PATSTAT or similar firm-level databases in different countries;
Private databases	Databases containing detailed records of actual technology transactions, information on inventors and firms, owned by technology marketplaces, patent exchanges, auction platforms, commercial banks and financial institutions.

patented and non-patented technologies, the duration of IP protection and the frequency of renewals or extensions also serve as signals of a technology's long-term commercialisation success and quality (Bessen 2008).

The emergence of big data and data analytics has made it increasingly feasible to track the evolution, adoption and public perception of technologies in real time, providing rich insights into their position within the technology lifecycle (Gao et al. 2013; Lin et al. 2021). The lifecycle stage can be identified through various dynamic indicators, such as trends in patent filings within specific IPC classes, publication counts in relevant research themes, forward citations to patents and academic works, patent abandonment rates, changes in user adoption metrics and public engagement as reflected in online searches, media mentions and social media trends. Additionally, financial and market-based characteristics, such as the growth in revenue, employment and venture capital investment, can signal whether a technology is in its growth, maturity or decline phase.

Measuring the readiness and risks of the enabling environment that delivers technology utility involves evaluating the availability, accessibility, affordability, preparedness and risks of the necessary infrastructure, regulatory conditions and complementary technologies. For example, the effectiveness of ICT technologies is closely tied to digital infrastructure, such as broadband speed and penetration, the number of internet and mobile phone users, 5G availability and national AI adoption rate (Kamga et al. 2023). Regulatory readiness can be proxied using composite indices measuring IP protection strength, regulatory quality enforcement, environmental regulations and ease of doing business. Additionally, the presence of sector-specific policy, such as AI legislation, pharmaceutical approval pathways or EV safety standards, reflects regulatory maturity. Competition dynamics, industry concentration, industrial sentiment index, trade policy changes (e.g., tariff and non-tariff measures) and ecosystem characteristics (e.g., technology clustering or innovation hubs like Silicon Valley) also contribute to the overall enabling environment and affect the potential market size. Many of these indicators can be collected from publicly available sources such as the World Bank, WIPO, national patent offices, OECD, UN agencies and national government websites, reports of research institutions such as The Network Readiness Index published by Portulans Institute and University of Oxford, as well as commercial data platforms such as Statista.

Finally, firm-level characteristics can serve as important proxies for team capability, future potential, sustainability and risk exposure in technology development and commercialisation. Measurable indicators of the R&D team, including R&D investment, the number of R&D personnel and the educational and research backgrounds of key inventors, help determine the team's technology development capabilities and the quality of the resulting innovations. Firm size, measured by employee counts or revenue, reflects financial strength and operational capacity (Moro et al. 2020) and its ability to exploit technological inventions (Dierickx and Cool 1989) while managing risks related to IP protection, upgrading and commercialisation (Ghosal and Loungani 2000). Firm age can indicate experience in navigating technology markets and managing innovation. Founder-related metrics, including the number of founders, age, gender, education and prior experience, can also provide insight into entrepreneurial and risk control abilities. The number of IP disputes measures the uncertainty in IP ownership and legal risks. Additionally, the number of funding rounds and the total amount of funding raised signal a firm's maturity and ability to successfully commercialise its technology. These data are widely available across commercial, government and open-access firm databases, offering a foundation for empirical analysis.

4.2 | Modelling and Prediction of Technology Value

Data from various sources can be cleaned, transformed and integrated to support the modelling and prediction of technology value. Two primary quantitative approaches are commonly employed in this context: econometric modelling and AI-based machine learning (ML) techniques.

The econometric approach is particularly useful for estimating the relationship between the four key attributes of technology utility and their impact on valuation, under pre-defined functional forms and theoretical assumptions. Widely used models include linear regression (e.g., ordinary least squares), time series models and panel data models. These methods allow us to identify and interpret the magnitude and direction of influence that individual indicators and attributes exert on technology value. Econometric models offer the advantage of transparency and interpretability, supporting causal inference when the underlying assumptions are met. However, they may have challenges capturing non-linear or high-dimensional interactions within the data and tend to have issues of omitted variable bias or overfitting in the presence of complex relationships.

In contrast, the ML approaches prioritise predictive accuracy over causal inference. These methods learn patterns from data with less reliance on prior assumptions about the functional form of relationships. ML algorithms are particularly effective when working with large-scale, high-dimensional datasets where relationships between variables are complex or non-linear (Athey and Imbens 2019; Mullainathan and Spiess 2017). Typically, the sample is split into training and test subsets, where the former is used to train the model and the latter to validate its out-of-sample predictive performance. Commonly used algorithms include Decision Trees, Random Forests, Gradient Boosting Machines and Neural Networks. These models can be optimised using techniques such as hyperparameter tuning, regularisation and cross-validation to improve predictive accuracy and mitigate overfitting.

Despite the strengths, a major concern of ML models is their 'black-box' nature, which makes it difficult to interpret how predictions are generated. However, recent advancements have improved the interpretability of ML models. Tools such as feature importance scores and SHAP (SHapley Additive exPlanations) values offer insights into the contributions of individual features to the model predictions, thereby enhancing transparency.

For technology valuation, a hybrid approach that combines ML and econometric techniques is employed to leverage the strengths of both methodologies, improving predictive performance while maintaining interpretability and theoretical rigour.

4.3 | AI-Powered Practical Applications in Technology Valuation, Transfer and Commercialisation

Our theoretical framework and empirical methodology have been effectively implemented and validated through a collaboration with OxValue.AI, a technology spin-off company from the University of Oxford. Based on the proposed framework, OxValue.AI has developed AI-powered technology valuation tools deployed across eight knowledge-intensive industrial sectors. Drawing on data from 16 sector-specific databases, the company leverages a massive dataset comprising approximately 150 million patents, 340,000 startup companies, 58 million inventors and over 200 million observations. From this extensive data infrastructure, hundreds of indicators are constructed to quantify the four key attributes of technology utility defined in our model.

To illustrate the practical application, we examine a case study involving a sample of 1426 ICT startup firms in California. The amount of fundraising secured by these startups is used as a proxy for the private market value of their patented ICT technologies. We apply both traditional econometric methods and ML algorithms to predict the technology value and evaluate the performance of each approach, as shown in Figure 4.

Using OLS regression, Figure 4a indicates that most predicted values fall within 15% of the actual fundraising values. The model achieves a strong R-squared value of 0.832, demonstrating the validity of our indicator framework and its explanatory power. In parallel, we apply a Feedforward Neural Network (FNN) as an ML method, training the model over 1000 epochs, with Mean Squared Error (MSE) as the loss function. As shown in Figure 4b, both the training and test R^2 scores converge to stable values of 0.877 and 0.866, respectively. These results suggest that the FNN model effectively captures the underlying patterns in the data while maintaining generalisability. The narrow gap between training and test R^2 indicates minimal overfitting, reinforcing the model's robustness in out-of-sample prediction.

In practice, AI tools can now automate the full valuation cycle, encompassing data collection, prediction and report generation. To scale and operationalise these predictive models, OxValue.AI has developed a fully digitalised valuation platform that harnesses the power of AI and big data. At the front end, a multimodal large language model (MML)-enabled chatbot interface facilitates user interaction by simulating human conversation, guiding users through the initial data collection process. The gathered information is then used to automate backend procedures, including real-time data retrieval via APIs for additional indicators, execution of predictive models and the generation of valuation results. Final outputs are automatically synthesised into detailed reports composed using ChatGPT APIs. These reports apply advanced natural language processing to summarise data, interpret model results and clearly present the valuation findings alongside key insights and contextual analysis tailored to clients.

This end-to-end digital workflow dramatically shortens the technology valuation timeline—from several weeks or even months in traditional practice (J.P. Morgan 2024; Patel 2024) to just a few minutes—while reducing costs to approximately 10% of the market average. By automating the entire process, the platform minimises human intervention and ensures consistency and efficiency. Although traditional valuators offer adaptability and contextual expertise, they are inherently constrained by cognitive limits, time pressure and information overload (Boyacı et al. 2024). In contrast, AI-powered systems enhance accuracy, scale and speed.

With real-time data retrieval capabilities, the valuations are based on the most current market and technology information available. Furthermore, the system's scalability also enables it to handle a large volume of valuations simultaneously. These innovations provide game-changing solutions in the valuation landscape, enabling quicker, more objective, accurate and affordable valuation services that not only accelerate decision-making but also facilitate faster technology transfer and international IP trade.

To meet diverse client needs, OxValue.AI offers three valuation packages tailored to different use cases within each industry: one for individual patents, one for research teams and another for startup firms. Between the year period 2022 to 2025, the platform has completed over 10,000 valuation cases, assisting startups, research institutions, venture capitalists, financial organisations, technology exchanges and government agencies in making strategic decisions related to technology transfer, acquisition, investment appraisal and commercialisation. These real-world applications underscore the practical relevance and global potential of our valuation framework and methodology, demonstrating its potential to drive digitalisation and expansion of international IP trade.

Overall, our methods bridge the longstanding gap between valuation theory and industrial practice. By embedding measurable indicators into a structured, interpretable theoretical framework and integrating them with state-of-the-art ML and AI techniques, we offer a solution to technology valuation that is theoretically and methodologically rigorous and practically applicable. This approach significantly improves transparency, efficiency and trust in technology markets, empowering IP transactions, informing strategic investment decisions and accelerating innovation diffusion across borders.

5 | Further Implications for International Trade in IPs

New technologies and digitalisation have transformed not only how we trade but also what we trade (González and Jouanjean 2017). On the one hand, new information industries have emerged, including services in big data analysis, cybersecurity and remote quantum computing (Oyewo et al. 2023). On the other hand, firms adopting advanced technologies are increasingly shifting towards knowledge-intensive production processes. Automation reduces the role of labour in determining comparative advantage in trade, making intangible assets and access to knowledge-based capital crucial for competitiveness. These shifts encourage knowledge-intensive assets, such as software, patents and data, to move more freely across borders and within global value chains (GVCs).

An AI-empowered valuation method based on technology utility can facilitate the digitalisation of trade worldwide, particularly concerning knowledge-intensive assets and IPs. First, these AI-driven valuation tools provide consistent, reliable and objective technology valuations at a low cost, helping to establish

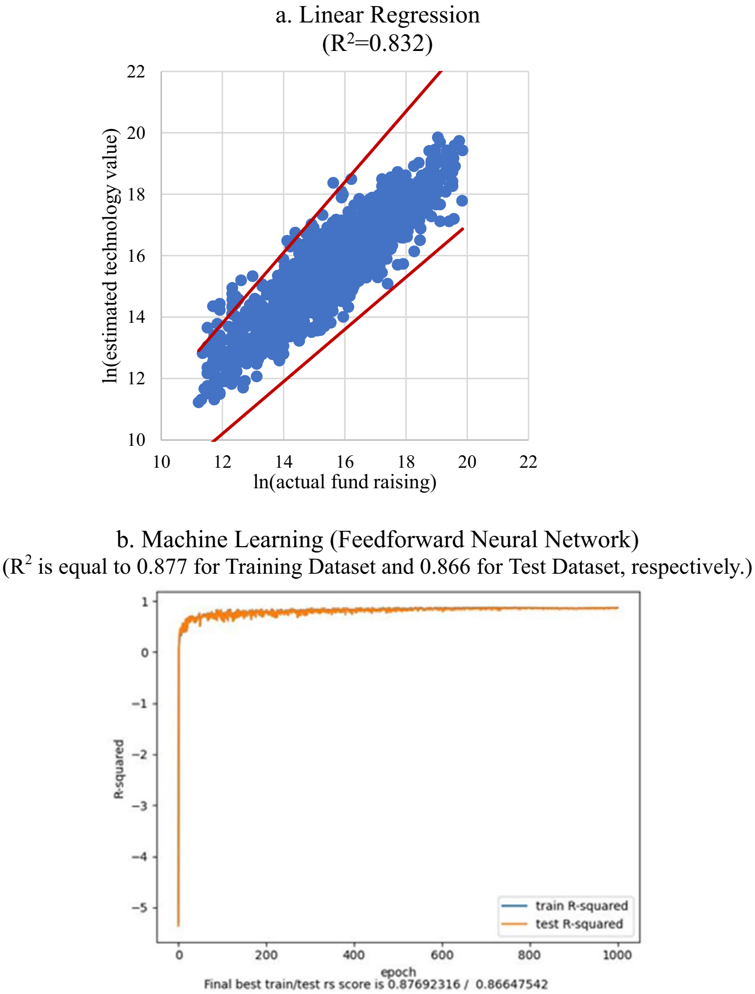

FIGURE 4 | Prediction performance between linear regression and machine learning for the value of technology of ICT startups in California, 2001–2022. (a) Linear Regression ($R^2=0.832$). (b) Machine learning (feedforward neural network). ($R^2=0.877$ for training dataset and 0.866 for test dataset, respectively). The sample contains 1426 startup firms (aged ≤5 years) with patented technology in the ICT sector from California, US, from 2001 to 2022 (observations = 2616). The amount of fundraising secured by these startups is used as a proxy for the private market value of their patented ICT technology. A set of indicators is used to capture the four attributes of the utility of technologies. The scattered dots in Figure 4a indicate the relationship between the actual fundraising, as a proxy of the monetary value of startups' technology, and the predicted value of technology. The two red lines are the upper and lower bounds within 15% of the actual values. A freedforward neural network is used for the ML method, training the model over 1000 epochs. *Source:* OxValue.AI. [Colour figure can be viewed at wileyonlinelibrary.com]

standardised benchmarks for IP valuations across borders. This standardisation reduces trade barriers in IP transfers and simplifies negotiations and trade agreements between firms and countries with varying IP valuation regulations.

Second, accurate, accessible and affordable valuation tools minimise knowledge asymmetry between buyers and sellers, likely increasing the volume of IP trade, particularly international trade in IPs. This will especially benefit smaller businesses and startups that often lack resources for extensive valuation. Big-data-backed valuation tools reduce reliance on subjective assessments, enhancing transparency in IP pricing and promoting fairer trade practices. Additionally, automated AI-based valuation tools can support the development of digital IP trading marketplaces or platforms, offering real-time IP valuations and enhancing IP transactions and market liquidity.

Third, these valuation tools facilitate IP transactions, mergers and acquisitions, commercialisation and investment globally. For buyers and investors, AI-empowered valuation tools based on objective data reduce the risk of over- or undervaluing IPs, while for sellers and IP creators, these tools strengthen bargaining power. Such tools help mitigate fraud cases, like that of Theranos, which claimed to offer breakthrough health technology without any published research in peer-reviewed biomedical literature (Ioannidis 2015). Low-cost and accurate valuation models also promote investment in knowledge-intensive industries, spurring further innovation and the creation of IPs and other knowledge-intensive products globally.

For instance, OxValue.AI has facilitated cross-border M&As in tech startups and supported UK IP commercialisation in China. It streamlined the valuation process for a Chinese biotech company acquiring a biotech startup in the UK by leveraging predictive analytics to assess the startup's financial health and projected growth, ensuring that the acquirer had a clear understanding of the investment's worth. Additionally, it assisted a UK software firm in assessing the value of its IP portfolio before seeking partnerships in China, enabling the firm to present a compelling case for its technologies. According to the founder of OxValue.AI, Prof. Xiaolan Fu, the company plans to establish an online platform for cross-border IP trade in cities across China and Southeast Asia.

Finally, in the long term, AI and big data-driven valuation tools can contribute to future reforms in international trade statistics. By providing real-time IP valuations, these tools reduce discrepancies and subjectivity associated with traditional IP valuations. OxValue.AI has also applied this utility-based valuation framework to other sectors, such as biopharma, medical devices, clean energy and resource-intensive industries. With access to large datasets and future advancements in digital tools, AI can differentiate value across all industries, leading to sector-specific valuations that improve trade statistics. A consistent methodology will enhance the comparability of trade statistics across countries, fostering harmonisation of valuation standards. Integrating IP trade more comprehensively into existing trade statistics may fundamentally influence the calculation of trade balances between countries. Overall, such valuation tools have the potential to shape reforms in global IP trade statistics, enabling policymakers to monitor and manage the trade of intangible assets and make more informed, strategic decisions.

6 | Conclusions

Ex ante technology valuation is critical not only for a firm's innovation investment and commercialisation process but also for cross-border IP transactions and trade in the era of digitalisation. Drawing on the utility theory of value and related literature in innovation economics and finance, we develop a framework that synthesises existing concepts into a cohesive model. The framework highlights that the value of technology is determined by its value in use, specifically, the utility it provides to consumers and society as a whole. This value is shaped by four intrinsic attributes: the nature and size of utility (e.g., functions and market), the quality of utility (e.g., novelty and reliability of technology, its life cycle position and team characteristics), the delivery of utility (e.g., readiness of the enabling environment and complementary technologies), and risks and sustainability of utility (e.g., risk, risk management and future potential). This framework is supported by evidence from a sample of ICT startups, leveraging objective data and AI-empowered prediction tools from OxValue.AI.

Overall, this study offers a new paradigm for valuing knowledge-intensive assets, bridging longstanding gaps in both theory and practice. We introduce a systematic framework to explain the value of technology and establish an empirical method for measuring this value using big data, econometric modelling and machine learning. Practically, we highlight the potential applications of AI-empowered valuation tools for technologies across diverse sectors. These digital tools bring substantial improvements, particularly in addressing the limitations of traditional valuation methods. Through AI's capacity for high-dimensional analysis, processes that were once challenging or even impossible become feasible, reducing knowledge asymmetries between buyers and sellers and facilitating negotiations, transactions and global trade in IP assets with unprecedented speed, low cost, precision and transparency.

This study provides valuable insights for researchers, managers and investors regarding digital transformation in improving intangible asset valuation and stimulating global IP trade. Many small firms and startups will benefit from these AI-empowered valuation tools, which make IP valuation accessible and affordable, fostering inclusivity in IP transactions and promoting further innovation. As these tools continue to develop and gain widespread application, this framework will contribute to future trade statistics reform, harmonising technology valuation standards and enhancing the comparability of trade metrics across borders. Overall, the utility theory valuation framework introduces not just a robust tool for practical IP valuation but also a transformative approach aligned with the rapid evolution of technology, digitalisation and globalisation. Additionally, this study provides insights for policymakers, who should understand the digitalisation of IP trade to develop trade policies that effectively respond to a digitally transformed knowledge economy.

Admittedly, this paper presents only an initial attempt to explore the theoretical foundations of IP valuation. Although the general framework proposed here may apply across industries, the value of technology is also influenced by industry-specific features. Future research should investigate how such characteristics affect technology value, examining the channels and extent to which market- and country-specific factors, such as institutions and culture, play a role in technology valuation.

We also acknowledge that AI-empowered valuation tools heavily rely on large datasets and machine learning algorithms, which present limitations. Data unavailability, particularly for emerging technologies or niche markets and issues with data accuracy, such as incomplete patent information, can affect valuation precision and reliability. Additionally, collecting sensitive information across borders raises privacy and regulatory compliance concerns, potentially limiting the data that these tools can access and process. AI models also have inherent limitations, such as the potential for biases inherited from training data and a 'black-box' nature that can obscure the rationale behind certain valuations, impacting user trust and raising concerns about transparency in decision-making. However, combining AI models with linear regression results or using interpretable machine learning techniques can improve the interpretability of the models. Although AI technologies overcome many human limitations and excel in making multidimensional comparisons, it is essential to recognise that human contextual knowledge and intuition are difficult to replicate. Human–machine collaboration remains crucial for optimising outcomes in AI-empowered valuation, as human expertise continues to play a critical role in nuanced, context-sensitive valuation tasks.

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Conflicts of Interest

The authors declare no conflicts of interst.

Data Availability Statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

Endnotes

[1] In this study, we focus on the evaluation of firm-level technology as a primary example. However, the model is designed to be adaptable and can be extended to assess the value of technology portfolios held by innovation teams, as well as individual technologies, such as a specific patent and software asset.

[2] In technology-intensive industries, early-stage fundraising value is primarily based on the technologies themselves, as these startup firms typically lack tangible assets (Cassar 2004) and have not yet accumulated significant other types of intangible assets, such as trademarks.

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