# Economics of Data Systematic Review for Planning Strategies in the InsurTech industry

**Claudio Bonvino and Marco Giorgino**
**Politecnico di Milano, Milan, Italy**
claudio.bonvino@polimi.it
marco.giorgino@polimi.it

**Abstract:** The knowledge of data enables exploring how value is created from data. Organizations' strategic planning becomes easier if the value of data is understood and adopted. Unless managers know how to use data, its exploitable value remains limited. Previous studies assessed either data dimensions such as volume, variety, velocity, veracity and granularity, or data management processes. However, many of these topics have been treated with a technical approach and only a few focused on the data value in management, strategy, and planning. The ubiquitous of data has allowed insurance incumbents and startups to exploit technologies, from which InsurTech, leveraging a unique data-driven proposition and often gaining a competitive advantage. The paper aims to explore the economics of data, enabling to strategically plan data management practices. It contributes to the management and strategy literature with an evidence-based systematic literature review that embraces the value generated by knowing data sources, data types, extended data dimensions, analyzes enabling technologies, and extends data management practices for reaching organizations' objectives in the InsurTech empirical context. In addition to further avenues of research, it provides managers with a theoretical data-valorization framework for data strategic planning, and institutions an overview for guiding the digital transformation. The novelty of this paper is the comprehensive focus on the economics of data at the intersection between traditional and emerging business models.

**Keywords:** data value, data knowledge, data management, strategic planning, InsurTech

## 1. Introduction

Organizations' strategic planning becomes easier if the value of data is understood and adopted. "By 2025, […] most employees will use data to optimize nearly every aspect of their work" (McKinsey, 2022). As reported by a recent special issue, scholars are increasingly interested in the relationship between competition, regulation and data management that allows scaling financial businesses in the new digital era (Giudici et al., 2021).

Data has been studied mainly technically. On the one hand, authors started connotating data dimensions as the 3Vs: volume, velocity, and variety (Laney, 2001), veracity (Goes, 2014), granularity (Aaltonen & Tempini, 2014; Yoo, 2015), portability, interconnectivity (Günther et al., 2017) and others ontological characteristics (Kitchin & McArdle, 2016). On the one hand, scholars proposed technical frameworks to process data in organizations (Alfaro et al., 2019; Lange & Drews, 2020; Faroukhi et al., 2020).

The benefits that organizations perceive as "value" depend on the alignment of their strategic goals with the usage of data (Ghoshal et al., 2014) and it is proven that its adoption could lead to achieving higher economic results (LaValle et al. 2011, McAfee and Brynjolfsson, 2012). The scattered background brings the need for a literature review that explores the value generated by the knowledge of data.

A key empirical context is the evolving insurance sectors, namely InsurTech: insurance plus technologies. Early signals of the term appears in 2015, driven by the implementation of advanced technologies in the FinTech industry (WEF, 2015, Zavolokina et al., 2016), whereas the first studies on InsurTech date 2017-2018 (Lanfranchi & Grassi, 2021). InsurTech perfectly combines three major ingredients: money (Dorfman & Cather, 2013), information (Muller, 1995), and technology. The technology is the major ingredient of InsurTech because it associates insurance services and products with advanced technologies. In less than a decade, information and technologies disrupted business models. The related innovations in business models in InsurTech can be a representative context for generalization of other evolving sectors. Specifically, "insurance companies have always been big users of data in analyzing and measuring the risks they take into insurance coverage, setting conditions for insurance policies and assessing the risk (accepted by insureds) as well as conditions for insurance contracts and claims. Insurers have strong analytic capabilities compared to their peers in other industries" (Njegomir et al., 2021). The proliferation of data has allowed insurance to embrace technologies to harness a unique selling proposition and competitive advantage over other market participants (Cortis et al., 2019). In the financial ecosystem, InsurTech can also help to improve existing products, services, and processes, as well as enable new business models (Nagle et al., 2020). Moreover, the insurance industry is strongly connected with society because it is based on customer risks and customer-insurance provider engagement and it is highly regulated (Al-Witwit & Ibrahim, 2020; Eling & Lehmann, 2018), giving this paper the chance to evaluate data regulation. InsurTech becomes an industry worth targeting for this paper's purpose.

The centrality of data in insurance is due to the ability of insurance companies to generate economic value from data usage; the exploitation of data can be understood only starting from its characteristics (McAfee & Brynjolfsson, 2012). Therefore, the paper investigates the following research question: "What are the economics of data that create value for a firm by using data strategically?". By answering this question, the work proposes a theoretical framework that connects the knowledge of data economics and related strategies to generate value. Scholars could be inspired in studying data value implications in strategy, management, and economics. Managers would be guided in their strategic action in the current digital transformation. Policymakers could drive policies for increasing competitiveness.

The paper is structured as follows: first, the authors highlight the methodology; second, they report the data knowledge pillars for generating value; then they resume the management practices into a data valorization framework; finally, the authors summarize how to use data strategically for long-term planning which brings to the implications and conclusions section.

## 2. Methodology

The authors explore the economics of data through an evidence-based systematic literature review. The aim is to investigate the economics of data and drive top management for well-informed decisions making (Campbell Collaboration, 2001). Many papers tried to study data by limiting the search strings with keywords such as "big" or "social", mainly for analytical studies but not for management. This paper's approach is novel because it assesses an industry and extracts the value generated from data. The review was organized in: planning, conducting and reporting (Tranfield et al., 2003), as per Figure 1. In the first stage, the team identified the need to review data associated with management practices by imposing a review protocol that contained: (i) data related documents in the (ii) InsurTech industry. The review panel adopted the keyword "InsurTech" in titles, keywords, and abstracts to maximize the sensitivity. The search was run in Scopus and Web of Science, as these databases contain a larger number of documents in the management and economics fields. Moreover, the search captured grey literature's documents (Godin et al., 2015) with a content-based approach. Authors applied the language filter of English. The selection of studies was run in double-blind. Finally, selected papers were organized in an extraction table. The assessment included all primary results (Pollock & Berge, 2018), investigating early trends – not limiting documents per quality.

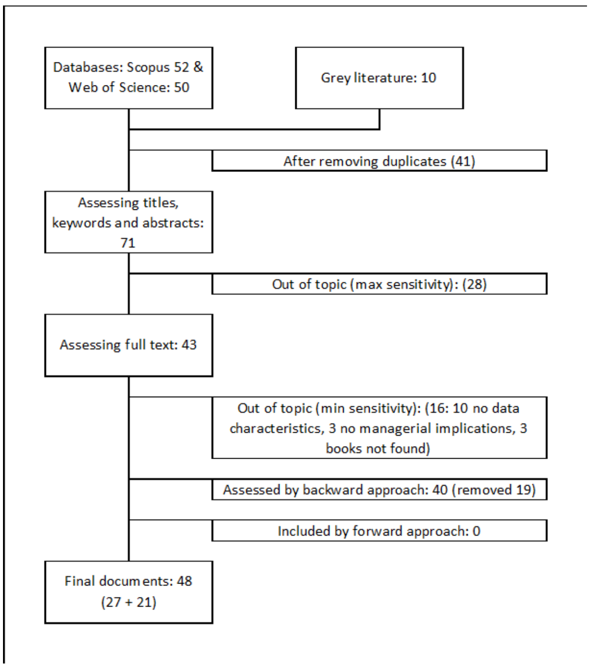


**Figure 1:** Systematic literature review of data in InsurTech

## 3. The economics of data in InsurTech

Data, datasets, or big data could interpret different traits but refer to a key input: data as a piece of a unit of information. The paper refers to them as synonymous to concentrate on the knowledge pillars of data that bring value. The InsurTech industry uses data in valuing the risks, setting policies, underwriting, and managing claims. Now, InsurTech organizations are covering specific needs, driven by the knowledge explored from data and extracted by three key pillars: data sources, data types, and data dimensions.

### 3.1 Pillar I: Data sources

Data sources refer to where the resource is held or stored (Sen, 2004), and they are public, private, exhaust, community or self-quantification (Gerard et al., 2014). Public data are held by public organizations. Private data are held by private organizations or individuals with private information and can be behavioral data, consumers' transactions, browsing, mobile usage or records. Data exhaust denotes passively collected data with zero value unless connected to other sources. They are the product of individuals' daily lives or inferences. Community data are generated by dynamic networks (e.g., social networks, consumers' reviews, voting buttons). Self-quantification data includes individuals' actions or behaviors (e.g., preferences), and they can be connected to psychology (Gerard et al., 2014).

Data sourcing can happen internally, externally or in hybrid ways. Internal sources are produced by an entity's device (Mai, 2018; Yu & Yen, 2020). External sourcing refers to data, often open, elaborated with external private or public organizations (e.g., collaborations, vendors, 3rd parties or service providers) (Mai, 2018; WEF, 2015; Yu & Yen, 2020). Hybrid sources of data can be those collected from public-private partnerships (OECD, 2016). Some institutions are fostering sources sharing for strategic purposes between governments and businesses (EC, 2020a). The present literature does not stand empirical studies on the economic value brought by data sourcing adoption and sharing.

### 3.2 Pillar II: Data types

The literature on data types is usually covered technically while knowing it with a management view could have strategic implications. Data types can be structured, semi-structured or unstructured. Structured data refers to traditional data, stored in tabular spreadsheets or relational databases, organized in variables, attributes, subjects, and time (Naik et al., 2008). Semi-structured data do not conform to relational databases but can be modified to structural forms. Unstructured data are most of today's data: text, photo, audio, video, clickstream, and sensor data (Ajah & Nweke, 2019; Lee, 2017). Unstructured data are often called alternative or unconventional data. The key role of these data elaborated from advanced technologies is the collection of behaviors and preferences, which enable weather and catastrophes forecasting, road analysis, and accident prediction among others (Cevolini & Esposito, 2020; Ching et al., 2020; Mai, 2018; Nagle et al., 2020; Njegomir et al., 2021; WEF, 2015; Xu & Zweifel, 2020). In numbers, structured data counts for 10-15%, semi-structured data for 5-10% and unstructured data about 80% (Christine Taylor, 2018; Gandomi & Haider, 2015; OECD, 2020). Unstructured data can be dimensioned into structural data.

Data and metadata – embedded data (Sen, 2004) – types management are pillars for knowledge discovery, and for subsequently planning insightful strategies (EU, 2018; Wilkinson et al., 2016). InsurTech organizations use the knowledge of data types for extracting value in daily activity and management strategic planning.

### 3.3 Pillar III: Data dimensions

The literature studied data dimensions technically. The state-of-the-art limitedly advanced on the value that the knowledge of data dimensions implicate in the management and strategy of organizations. The paper reviews data dimensions, extracts managerial implications in InsurTech, and proposes avenues for research (Table 1).

**Table 1**: Data dimensions generalization

| Data dimensions | InsurTech key implications | Avenues for research |
|---|---|---|
| Volume | Data enrichment; Insightful and accurate analyses; Data collection boosts business growth | Economic value |
| Velocity | Interconnectivity; Real time; Latency | Economic value |

| Data dimensions | InsurTech key implications | Avenues for research |
|---|---|---|
| Variety | Solve hidden relationships or inconsistencies | Economic value |
| Veracity | Accuracy; Truthfulness; Quality | Economic value |
| Accessibility | Findability; Interoperability; Reusability; Legal prevention: compliance | Economic value; Entities collaboration vs cooperation |
| Granularity | Completeness; Rareness; Uniqueness | Economic value |
| Sharing | Strategic management; Nonrivalry; Portability | Economic and societal value; Entities collaboration vs cooperation |
| Ownership | Personal vs non-personal; Ethics; Trust | Economic value; Behavioral data from connected devices: issues related to the aggregation and ownership |
| Privacy | Reputation; Enrichment; Customer protection | Economic & societal value; Paying for preserving privacy; Role of trust; Entities collaboration vs cooperation |
| Regulation | Compliance; Availability; Security | Tightness of regulation |
| Central vs Distributed | (Im)mutability; Depletion | Business, economic & societal value |

The *volume* of data refers to the size of data collected. Scholars agree on its importance (Cortis et al., 2019; Laney, 2001) and successful entrepreneurs know how it can translate into business growth (IDC). Data volume sums historical (Gramegna & Giudici, 2020), real-time and analyzed data. In InsurTech, data volume is used to evaluate, predict, understand, visualize, personalize and price services and products, engage with customer, modify customer decisions, assess, extract information, explain and create policies (Al-Witwit & Ibrahim, 2020; Ching et al., 2020; Njegomir et al., 2021; Tereszkiewicz & Południak-Gierz, 2021), and signal early warnings. Data volume can have a strategic advantage for the owner, which increases with advanced technologies (Cevolini & Esposito, 2020; EC, 2020b; Njegomir et al., 2021). Although a small number of Big Tech players such as Amazon, Apple, Facebook and Google hold a large part of the world's data, future players are yet to be decided because historical data collected by incumbents is yet fully exploited and start-ups with advanced technologies could easily scale these data (Eling & Lehmann, 2018; Mai, 2018). "The sources of competitiveness for the next decades in the data economy are determined now" (EC, 2020a), and the fastest collection can boost the new winners.

The *velocity* dimension of data refers to the pace of interactions (Laney, 2001) or analyses (Cortis et al., 2019; OECD, 2020) – e.g., extraction, integration, reorganization, access and routing (Laney, 2001). During the years the pace of data increased enabling real-time access. (Yu, 2008) Real time information are relevant, but decision makers should evaluate data for short- and long-term performances.

In InsurTech, organizations use (near) real time for personalized offers at the most prone audience at the right time and price, by processing a person-based contract or customer monetary rewards based on clients' data, detecting frauds or assessing and managing risk-portfolio; while revamping the traditional insurance products (Cortis et al., 2019; Gramegna & Giudici, 2020; Mai, 2018; Stoeckli et al., 2018; Talonen et al., 2021; Tereszkiewicz & Południak-Gierz, 2021; WEF, 2015; Yu & Yen, 2020). In risk management, practices involve time value, where "it is important to adjust dollar values to reflect the earning of interest"(Rejda, 2019).

The data *variety* dimension values the number of sources and types (Anshari & Alas, 2015; Cortis et al., 2019; Laney, 2001; Lee, 2017), because the latter unveil hidden relationships or inconsistencies. "High variety is when there is structural heterogeneity in the dataset" (OECD, 2020).

In InsurTech, data variety has been increasing by merging data of public entities and enterprises (Njegomir et al., 2021). Moreover, "many data sources ensure the deploy of data analytics for evidences on significant correlation or phenomenon" (EC, 2018).

The *veracity* relates to the accuracy, truthfulness, and quality of this digital resource (Goes, 2014; Cortis et al. 2019; Malgieri & Custers, 2018). In the past, it was overlooked by multiple sources, whereas today is a pressing issue because of false information. Data accuracy is a factor of previous dimensions, and it can be verified with advanced AI tests (Al-Witwit & Ibrahim, 2020; EC, 2020b; Gramegna & Giudici, 2020; Marafie et al., 2018), and ensured with data management tools (Rejda, 2019). Moreover, accuracy can be increased with a series of validity checks (e.g., sample representativeness, sample dimension, sample corrections), triangulation of available information, or also relying upon experts' experience.

In InsurTech, the "risk may be reduced by application of the law of large numbers by which an insurer can predict future loss experience with greater accuracy" (Rejda, 2019). Thanks to data accuracy, policyholders could be priced accordingly to their behaviors, although certain individuals fill out (Cortis et al., 2019).

The *accessibility* stands for standardized, free, open, and authenticated and authorized procedure. Accessible data are often related with findable, interoperable, and reusable principles (EC 2018). Legal interoperability – data compliance – must be verified (e.g., anonymization) for ensuring the economic value for humans and machines (EC, 2020a; Tereszkiewicz & Południak, 2021; Wilkinson et al., 2016). Data accessibility could threaten market players, customers, and innovation. In Europe, it led to the Payment Systems Directives, proposing open banking and open finance as a new ecosystem (EC, 2020a). In InsurTech, there are multiple example of collaboration between incumbents and start-ups (Stoeckli et al., 2018), which value is not studied in depth. Given that insurance aims at estimating risks, having access to large data has a relevant role (OECD, 2020).

The literature lacks studies on data *granularity*, despite its empirical evidence. Data granularity is the level of extractable detail (e.g., environment, entity, decision making, preferences). Malgieri & Custers (2018) identify granularity implications such as completeness, rareness, and uniqueness as data monetary value.

In InsurTech, granularity can fine-tune the risk classification, which could modify premiums for some consumers as well as exclude others from the offerings (OECD, 2020; WEF, 2015).

The data *sharing* dimension lies in how entities transact own data. Digitalization eroded transaction costs, which became almost free; for example in exchange for a discount (Nagle et al., 2020; Saliba et al., 2021). InsurTech businesses evidence that sharing standardized data can create an ecosystem of "highly connected operations" (Yu & Yen, 2020), where open finance stimulates innovation (EC, 2020a).

Sharing data multiplicate the effect of having only own data, but the authors did not find studies on the effect of economic value (WEF, 2015). In management, data sharing could be investigated empirically addressing strategic alliances, cooperation-competition dynamics (Eling & Lehmann, 2018; Mai, 2018; OECD, 2020). For example, Lapetus Solutions, a US-based InsurTech start-up, have developed an AI system and is partnering with life underwriters to provide quotations using facial analytics to foster engagement in the sale and claim processing (Cortis et al., 2019). Data sharing implies a key characteristic of data: the nonrivalry. Differently from any other non-fungible uses, data could be used and reused if the access is ensured. Entities have the choice of sharing certain information: portability.

Data *ownership* focuses on the source of the data and the entity storing it (Sen, 2004). The ownership strongly links with the difference between personal and non-personal data. They are often aggregated in anonymized or pseudonymized forms. However, if technologies allow this data to be traced back to the user, it falls under the logic of personal data. Ethically, entities should ask the consent to data owners prior to using their data. A key point for InsurTech industry – and not only – is the ability to process data algorithmically that enables knowing more information than owners. Consumers' trust was identified as an important issue. In this sense, companies could give customers greater control of their own personal data (Talonen et al., 2021). Further research requires studies on the ownership of behavioral data sourced from connected devices and on the ownership of aggregated data (WEF, 2015).

The data *privacy* dimension is in the current debate of scholars, specifically addressing individuals, firms, and governments (Lee, 2017). Previous works imply that individuals are rational and able to share the optimal amount of information (Stigler, 1980; Posner, 1981). However, Acquisti et al. (2013) "raise the issue of individuals' abilities to optimally navigate issues of privacy". Private data are those that could violate an entity – individuals and organizations – information rights and values (e.g., reputation) (Rejda, 2019). Data enrichment such as data profiling must protect customers (Njegomir et al., 2021), and should prevent unfair practices related to ethics, ethnicity, gender, religion and belief discrimination (EC, 2020b; Rejda, 2019). In InsurTech, data privacy should ensure customer coverage (Tereszkiewicz & Południak-Gierz, 2021) with anonymization and processing techniques (Stoeckli et al., 2018; EC, 2020b; Tereszkiewicz & Południak-Gierz, 2021).

The *regulation* dimension of data protects fundamental rights of consumers (e.g., data privacy, data protection - EC, 2020a), discrimination, unfair contracts (Tereszkiewicz & Południak-Gierz, 2021) or unfair pricing (Al-Witwit & Ibrahim, 2020; Rejda, 2019). Entities should be compliant legally and/or ethically depending on countries regulations, accepting requests to destroy data with eventual economic loss. Data regulation should consider potential issues such as accessibility, market power imbalance, data governance, data infrastructure and technologies, empowering individuals to exercise their rights, skills and data literacy, and risk assessment. Moreover, the integration of regulated and less regulated insurance-related data “might be an efficient way to increase customer engagement” (Stoeckli et al., 2018). “Depending on regulation and willingness to share personal information, asymmetries could become smaller or larger […] regulators must define how and where they have to intervene”, especially in fields such as InsurTech where the use of data can be beneficial (Eling & Lehmann, 2018). Organizations should abide rules, by taking necessary measures to minimize the security risks involved (Saliba et al., 2021).

Data *mutability* is an emerging dimension that considers if the information is collected, stored, and maintained in a centralized or decentralized way, from which it derives the easiness to modify an original data. Centralized data is in a server or cloud (Eling & Lehmann, 2018). Decentralized data is owned on local devices, digitally connected, that validate the information by a consensus of devices. Decentralized technologies such as blockchain are driving this change also with the concepts of immutability and depletion. For immutability, data is transparently stored in ledgers and cannot be modified - unless overwriting it; for depletion, data is unique, and it does not need to be copied across devices.

In InsurTech, this dimension helps in checking legal requirements – according to underwriting purpose to secure information with consensus processes (Ching et al., 2020; Eling & Lehmann, 2018). This dimension requires further research in terms of business, economic and societal value.

## 4. Data enabling technologies

Advanced technologies such as data analytics (e.g., artificial intelligence, machine learning, neural network), Application Programming Interfaces (API), cloud and blockchain are driving to innovative apps, models, and online platforms. “Particularly, in banking and insurance sectors, technologies are disrupting for a decade. Every year, new things and new and innovative styles of operations are taking place in these sectors in the form of FinTech and InsurTech” (Ratnakaram et al., 2021).

By reviewing the InsurTech industry, technological innovations alter risk parameters by enriching traditional data with unconventional data. Technology and data enable a more fine-grained risk assessment by insurance providers. Thanks to telematics devices (e.g., internet of things devices, wearables, and mobiles), people live in a connected world providing a large amount of data. Vehicles, houses, and factories are digitally equipped making them programmable, addressable, sensible, communicable, memorable, traceable, and associable (Yoo, 2010). Without adequate, relevant, timely and complete information, it would be almost impossible for insurance companies to provide insurance services on a sustainable basis (Njegomir et al., 2021).

The literature well covers technologies technically. For the scope of data management and strategic planning, the technologies are key enablers for the creation of data value. Technology’s added value is the ability to enable compliance, transparency, accuracy, monitoring and updating and identifiability. Organizations’ planning requires individuals with digital competencies – currently scarce resource – for enabling data value creation.

## 5. Data management for strategic planning in InsurTech

The data economy with its pillars has strongly transformed the activities of organizations in many industries. Limited studies investigated how data and its management have impacted organizations’ strategic planning. In the financial ecosystem, insurance integrated slowly innovation since its early origins. Over the past decade, advanced technologies integrated and transformed the insurance business. Traditionally, policies have been priced based on predictions using historical data and sophisticated statistical models (WEF, 2015). Historical information comprehended static data provided by customers through papers or third-party data, including historical data and predictive indicators. Aggregated data enabled the identification of risk and the customers’ premium. After contracting the policy, customers and insurers mostly did not interact until renewal or claims’ request. Today, the majority of InsurTech organizations are not completely transforming commercial lines of insurance but are more focused on enabling or extending them (Njegomir et al., 2021). With the increased value of data and technologies, insurers can track and refine customers’ risk profiles, develop new based-needs services or products, offer and price them in a personalized way, preventively engage with customers, and process claim management and legal activities automatically. Telematics can collect usage and behavioral data of customers in real-time or near-real-time. Data management is at the core of the value creation of data and embraces the transformational process organizations are living. Integrating previous sections with Stoeckli et al., (2018), characteristics and transformational capabilities of InsurTech innovations explore the understanding of the value creation in a digital world that managers should consider in their strategic planning (Table 2).

**Table 2:** Data management strategic planning practices in InsurTech starting from Stoeckli et al., (2018)

| **Strategic planning practices in InsurTech** | | |
|---|---|---|
| Adjustment behavior/need | Digital identification | Loss mitigation |
| Aggregation | Digital notification | Nutrition data (enrich) |
| Automated fraud detection | Digital processing | Predictive prevention |
| Automated processing | Digital submission | Pricing (Usage/behavior/reward) |
| Automated verification | Digital transaction | Proactive warnings |
| Data enrichment | Digitalized offer | Recovery service |
| Digital adjustment | Distribution | Service provisioning at demand |
| Digital administration | Driving data | Simplified offer |
| Digital advisory | Individualized offer | Situational/Flexible offer |
| Digital conversation | Integration | Vitality data (live) |

The evidence-based review allows for defining a strategic planning framework that organizations can adopt to generate value from data, which could determine increasing revenues and therefore economic value for the organizations. The organization would require data knowledge which therefore evaluates the economics of data based on the three data pillars: sources, types, and dimensions. Data sources enable the identification of the origin of organization's datasets, available or potentially available. Data types drive the exploitation of organization resources, which could be both objective and subjective. Based on the origins and types of the digital resource, the data dimensions can be exploited to plan the objectives organizations aim at achieving. Then, by combining strategically data knowledge with investments in advanced technologies (data enablers), managers can plan their data management to make forward-looking decisions for cooperating-competing in the market. Managers should govern data for translating data knowledge into economic value (Figure 2).

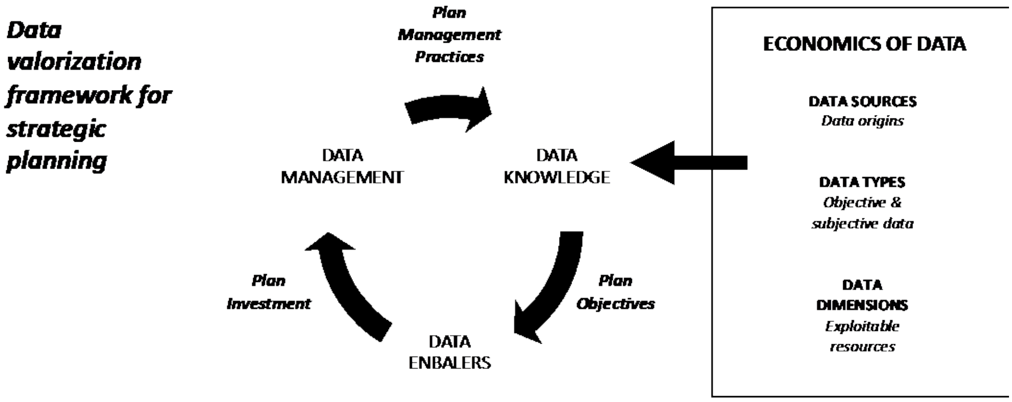


**Figure 2:** Data valorization framework for strategic planning

## 6. Conclusion

The review identifies three knowledge pillars for the creation of value from data: sources, types, and dimensions. Together with advanced technologies, these enable successful data management that requires strategic planning of resources, technologies, and practices. The paper answers the research question by providing (i) a novel comprehensive view of the data economics that brings value from data: the pillars; (ii) the extended data dimensions, essential for depicting the organizations' objectives; (iii) a theoretical data valorization framework that enables generating value strategically planning resources, technologies, and management practices. The authors believe the outcomes of the research in the InsurTech industry could be representative of other data-driven industries.

Limits of the work can be the limited number of academic papers extracted with "InsurTech" and the documents' quality. However, the literature review does not limit keywords for evidencing practices and emerging trends. Further studies can evolve on the impacts of data knowledge on activities of the value chain, and bring a more theoretical structure (e.g., knowledge management theory).

The current literature offers managers to assess and expand their data strategies, financiers to know the determinants of data value in data driven organizations, and policymakers to address guidelines for competitiveness. Altogether, the work contributes to data knowledge that enables the planning of strategic data management practices in the digital era.

## References


Acquisti, A., John, L. K., Loewenstein, G., Acquisti, A., John, L. K., & Loewenstein, G. (2013). What Is Privacy Worth? *The Journal of Legal Studies*, *42*(2), 249–274.

Ajah, I. A., & Nweke, H. F. (2019). Big data and business analytics: Trends, platforms, success factors and applications. *Big Data and Cognitive Computing*, *3*(2), 1–30.

Al-Witwit, S. S. I., & Ibrahim, A. A. (2020). Improving operational efficiency of government using artificial intelligence. *IOP Conference Series: Materials Science and Engineering*, *928*(2).

Alfaro, E., Bressan, M., Girardin, F., Murillo, J., Someh, I., & Wixom, B. H. (2019). BBVA's data monetization journey. *MIS Quarterly Executive*, *18*(2), 111–128.

Alshboul, Y., Wang, Y., Nepali, R.K., 2015. Big data lifecycle: threats and security model. *Proceedings of the Twenty-First Americas Conference on Information Systems*, Puerto Rico, August 13–15.

Anshari, M., & Alas, Y. (2015). Smartphones habits, necessities, and big data challenges. *Journal of High Technology Management Research*, *26*(2), 177–185.

Badr, Y., Mohamed, N., & Mohamed, A. (2018). Recent Trends in Big Data Analytics Towards More Enhanced Insurance Business Models. *Int. J. of Computer Science and Information Security*, *15*(12), 39–45.

Campbell Collaboration (2001). http://campbell.gse.upenn.edu/about.htm.

Cevolini, A., & Esposito, E. (2020). From pool to profile: Social consequences of algorithmic prediction in insurance. *Big Data and Society*, *7*(2).

Ching, K. H., Teoh, A. P., & Amran, A. (2020). A Conceptual Model of Technology Factors to InsurTech Adoption by Value Chain Activities. *2020 IEEE Con. on E-Learning, e-Management and e-Services, IC3e 2020*, 88–92.

Christine Taylor. (2018). Structured vs. Unstructured Data. *Datamation*, 67891.

Cortis, D., Debattista, J., Debono, J., & Farrell, M. (2019). InsurTech. In *Disrupting Finance* (pp. 95–128).

Dorfman M. S. & Cather D. A. (2013) *Introduction to Risk Management and Insurance*, 10th Edition. Pearson

Eling, M., & Lehmann, M. (2018). The Impact of Digitalization on the Insurance Value Chain and the Insurability of Risks. *Geneva Papers on Risk and Insurance: Issues and Practice*, *43*(3), 359–396.

European Commission. (2018). Turning fair into reality. In *European Commission* (Issue November).

European Commission. (2020a). A European Strategy for Data. In *European Commission*. https://ec.europa.eu/info/sites/info/files/communication-european-strategy-data-19feb2020_en.pdf

European Commission. (2020b). On Artificial Intelligence - A European approach to excellence and trust EN. In *European Commission* (Vol. 53, Issue 9).

Faroukhi, A. Z., Alaoui, I. El, Gahi, Y., & Amine, A. (2020). An adaptable big data value chain framework for end-to-end big data monetization. *Big Data and Cognitive Computing*, *4*(4), 1–27.

Gandomi, A., & Haider, M. (2015). Beyond the hype: Big data concepts, methods, and analytics. *International Journal of Information Management*, *35*(2), 137–144.

Gerard, G., Haas, M. R., & Pentland, A. (2014). From the editor: Big data and management. *Academy of Management Journal*, *129*(2), 321–326.

Giudici G., Grassi L, and Momtaz Paul P. (2021). Special issue Scaling Up the Fintech Business: Competition, Regulation & Data Management. *Journal of Economics & Business*

Godin, K., Stapleton, J., Kirkpatrick, S. I., Hanning, R. M., & Leatherdale, S. T. (2015). Applying systematic review search methods to the grey literature: A case study examining guidelines for school-based breakfast programs in Canada. *Systematic Reviews*, *4*(1), 1–10.

Goes, P.B., (2015). Big data – analytics engine for digital transformation: where is IS? *Proceedings of the Twenty-First Americas Conference on Information.* Puerto Rico, August 13–15.

Ghoshal, A., Larson, E.C., Subramanyam, R., Shaw, M.J., 2014. The impact of business analytics strategy on social, mobile, and cloud computing adoption. *Proceedings of the Thirty Fifth International International Conference on Information Systems*, Auckland, New Zealand, December 14–17.

Gramegna, A., & Giudici, P. (2020). Why to buy insurance? An explainable artificial intelligence approach. *Risks*, *8*(4), 1–9.

Günther, W. A., Rezazade Mehrizi, M. H., Huysman, M., & Feldberg, F. (2017). Debating big data: A literature review on realizing value from big data. *Journal of Strategic Information Systems*, *26*(3), 191–209.

International Monetary Fund, 2019. *The Economics and Implications of Data: An Integrated Perspective.* [Online] https://www.imf.org/en/Publications/Departmental-Papers-Policy-Papers/Issues/2019/09/20/The-Economics-and-Implications-of-Data-An-Integrated-Perspective-48596

International Data Corporation, 2020. *Rethink Data.* [Online] https://www.seagate.com/files/www-content/our-story/rethink-data/files/Rethink_Data_Report_2020.pdf

Jones, C. I., & Tonetti, C. (2020). Nonrivalry and the Economics of Data. *American Economic Review*, *110*(9), 2819–2858.

Kitchin, R., McArdle, G., 2016. What makes big data, big data? Exploring the ontological characteristics of 26 datasets. Big Data Society 3 (1), 1–10.

Laney, D. (2001). 3D Data Management: Controlling Data Volume, Velocity, and Variety. *Application Delivery Strategies*, *70*(5), 16.

Lanfranchi, D. & Grassi L. (2021). Translating technological innovation into efficiency: the case of US public P&C insurance companies. *Eurasian Business Review,* 11:565–585.

Lange, H. E., & Drews, P. (2020). From ideation to realization: Essential steps and activities for realizing data-driven business models. *Proceedings - 2020 IEEE 22nd Con. on Business Informatics, CBI 2020*, *2*, 20–29.

LaValle, S., Lesser, E., Shockley, R., Hopkins, M.S., Kruschwitz, N., 2011. Big data, analytics and the path from insights to value. *MIT Sloan Manage. Rev.* 52 (2),21–32.

Lee, I. (2017). Big data: Dimensions, evolution, impacts, and challenges. *Business Horizons*, *60*(3), 293–303.

Mai, H. (2018). Preface: Fin- & Insuretech. In *Springer*.

Malgieri, G., & Custers, B. (2018). Pricing privacy – the right to know the value of your personal data. *Computer Law and Security Review*, *34*(2), 289–303.

Marafie, Z., Lin, K. J., Zhai, Y., & Li, J. (2018). Proactive fintech: Using intelligent IoT to deliver positive insurtech feedback. *Proceeding - 2018 20th IEEE International Conference on Business Informatics, CBI 2018*, *2*, 72–81.

McAfee A., & Brynjolfsson E. (2012). Big data: The management revolution. *Harvard Business Review*, *90*(10), 4

McKinsey. (2022). *The data-driven enterprise of 2025*. Retrieved from https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/the-data-driven-enterprise-of-2025

Muller, W. (1995). Informational products. *Zeitschrift fur Betriebswirtschaft*, 65, 1017–1044.

Nagle, F., Seamans, R., & Tadelis, S. (2020). Transaction Cost Economics in the Digital Economy: A Research Agenda. *SSRN Electronic Journal*.

Naik, P., Wedel, M., Bacon, L., Bodapati, A., Bradlow, E., Kamakura, W., Kreulen, J., Lenk, P., Madigan, D. M., & Montgomery, A. (2008). Challenges and opportunities in high-dimensional choice data analyses. *Marketing Letters*, *19*(3–4), 201–213.

Njegomir, V., Demko-Rihter, J., & Bojanić, T. (2021). Disruptive technologies in the operation of insurance industry. *Tehnicki Vjesnik*, *28*(5), 1797–1805.

OECD (2016), "Public-Private Partnerships for Statistics: Lessons Learned, Future Steps: A focus on the use of non-official data sources for national statistics and public policy", *OECD Development Co-operation Working Papers*, No. 27, OECD Publishing, Paris.

OECD (2020). The Impact of Big Data and Artificial Intelligence (AI) in the Insurance Sector. *OECD*, 36. www.oecd.org/finance/Impact-Big-Data-AI-in-the-Insurance-Sector.htm.%0A

Pollock A. & Berge E. (2018) How to do a systematic review. *International Journal of Stroke.* Vol. 13(2) 138–156

Posner R. A. (1981) The Economics of Privacy. T*he American Economic Review.* (Vol. 71, No. 2)

Ratnakaram, S., Chakravaram, V., Vihari, N. S., & Vidyasagar R., G. (2021). Emerging Trends in the Marketing of Financially Engineered Insurance Products. *Advances in Intelligent Systems and Computing*, *1270*, 675–684.

Rejda, G. (2019). Principles of Risk Management and Insurance. In *Pearson Education* (Vol. 53, Issue 9).

Saliba, B., Spiteri, J., & Cortis, D. (2021). Insurance and wearables as tools in managing risk in sports: Determinants of technology take-up and propensity to insure and share data. *The Geneva Papers on Risk and Insurance - Issues and Practice*, *0123456789*.

Sen, A. (2004). Metadata management : past , present and future. *Decision Support Systems*, *37*, 151–173.

Stigler G. J. (1980) An introduction to Privacy in Economics and Politics. *The Journal of Legal Studies*, 9 623-44.

Stoeckli, E., Dremel, C., & Uebernickel, F. (2018). Exploring characteristics and transformational capabilities of InsurTech innovations to understand insurance value creation in a digital world. *Electronic Markets*, *28*(3), 287–305.

Talonen, A., Mähönen, J., Koskinen, L., & Kuoppakangas, P. (2021). Analysis of consumers' negative perceptions of health tracking in insurance – a value sacrifice approach. *Journal of Information, Communication and Ethics in Society*, *825215*.

Tereszkiewicz, P., & Południak-Gierz, K. (2021). Liability for incorrect client personalization in the distribution of consumer insurance. *Risks*, *9*(5).

Tranfield, D., Denyer, D., & Smart, P. (2003). Towards a Methodology for Developing Evidence-Informed Management Knowledge by Means of Systematic Review* Introduction: the need for an evidence- informed approach. *British Journal of Management*, *14*, 207–222.

Van Aken, J. (2001). Management Research Based on the Paradigm of the Design Sciences: The Quest for Field Tested and Grounded Technological Rules, Working Paper 01.1, *Eindhoven Centre for Innovation Studies*, Eindhoven University of Technology, Eindhoven.

Wedel, M., & Kannan, P. K. (2016). Marketing analytics for data-rich environments. *Journal of Marketing*, *80*(6), 97–121.

Wilkinson, M. D., Dumontier, M., Aalbersberg, Ij. J., Appleton, G., Axton, M., Baak, A., Blomberg, N., Boiten, J. W., da Silva Santos, L. B., Bourne, P. E., Bouwman, J., Brookes, A. J., Clark, T., Crosas, M., Dillo, I., Dumon, O., Edmunds, S., Evelo, C. T., Finkers, R., … Mons, B. (2016). The FAIR Guiding Principles for scientific data management and stewardship. *Nature*, *3*, 1–9.

World Economic Forum. (2015). The Future of Financial Services. In *World Economic Forum* (Issue June).

Xu X., & Zweifel, P. (2020). A framework for the evaluation of InsurTech. *Risk Management and Insurance Rev.*, *23*(4), 305–329.
Yoo Y. (2010). Computing in everyday life: A call for research on experiential computing. MIS Quar., 213–231.
Yoo Y. (2015). It is not about size: a further thought on big data. *J. Inform. Technol.* 30 (1), 63–65.
Yu, J., & Yen, B. (2020). Re-think insurance: A new perspective of InsurTech. *Proceedings of the International Conference on Electronic Business (ICEB)*, *2020-Decem*, 386–397.
Yu, L. (2008). The Downside of Real-Time Data. *MITSloan Management Review*, *50105*, 8–11.
Zavolokina, L., Schwabe, G., & Dolata, M. (2016). FinTech - What's in a name? *Thirty Seventh International Conference on Information Systems*, *May 2011*, 10–11.