RELATION OF DATA GOVERNANCE, CUSTOMER-CENTRICITY AND DATA PROCESSING COMPLIANCE

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Abstract

Compliance costs are significant, and data related regulations are more frequent. The study argues if compliance spending can also generate additional value, as just a minimal regulation requirements fulfilment is not by any means achieving a competitive advantage. To test the hypotheses, a quantitative method with Structural Equation Modelling and Partial Least Squares (PLS) in the SmartPLS tool is used. The empirical data is collected from 98 data management professionals involved in recent European Union and General Data Protection Regulation (EU GDPR) projects associated with party data in larger organizations across Europe. The study suggests that Data Governance Span (DGS) leads to the increase of both data compliance related variables - Data Compliance Innovation (DCI) and Privacy Project Efficiency (PPE) - at the same time. However, its effect on the increase of Data Compliance Innovation (DCI) is weaker than the effect on the increase of Privacy Project Efficiency (PPE). Customer-Centric Orientation (CCO) is discovered to be an underlying mechanism of the relationship between Data Governance Span (DGS) and Data Compliance Innovation (DCI).

Implications for Central European audience: Firms in Central and Eastern Europe (CEE) did not use innovation enough in data compliance. DCI is the lowest in the CEE region DGS1 is the second lowest in CEE compared to all-regions-average. DGS1 refers to the business stakeholder involvement in the formal engagement, which assumes their responsibility.

Keywords: data governance; data compliance; organizational design; customer-centricity; leadership

JEL Classification: M15, M21

Introduction

Compliance costs are significant in regulated industries and mainly justified and considered just as a necessary cost of staying in business. Data related regulations are more frequent, and companies will be asking for permission to collect data considerably more often while at the same time providing more transparency on what they do with the data afterwards. Minimal regulation requirements fulfilment is not by any means achieving a competitive advantage. Ideally, the compliance effort, if done right, should lead to better efficiency and innovative new business initiatives.

The study examines the impact of data governance horizontal and vertical span on innovation in compliance management when it comes to interaction with the customer. The impact will be considered through a mediating role of customer-centric organizational orientation. In parallel, the impact of the same data governance span on compliance management operational efficiency is explored in the implementation of privacy accountability processes.

The work will operationalize the competitive advantage related and self-contradicting dimensions of GDPR through two constructs: Data Compliance Innovation (DCI) and Privacy Project Efficiency (PPE). The GDPR, regulating the processing and use of personal data in the EU, makes companies review and upgrade their existing policies, procedures, and practices to ensure compliance. Kim et al. (2008) suggest that while usually seen as self-contradictory goals, enjoying the benefits of data utility while fulfilling data compliance requirements and protecting privacy might be still possible. The use of regulation as an opportunity to engage with customers in a new way and to innovate alongside that way - could be a differentiator in the market. The proposed changes are a chance for businesses to gain greater insight into their customers' needs (Sawhney et al., 2005). Hahn et al. (2018) and Myles (2015) argue that data compliance regulations can be the platform for the creation of new business propositions for customers while increasing internal return on investment in such data. Likewise, the advantage could be gained with the efficiency and performance of the necessary compliance project. Establishing organizational-wide roles, accountability for privacy protection and appropriate use of personally identifiable information is one of the key project activities in GDPR (Charlesworth & Pearson, 2013).

The organizational practice-driven information governance dimension of this research is the Data Governance Span (DGS) construct. As per Korhonen et al. (2013), relating organizational approaches or practices to the field of data, including data compliance, leads to the data governance concept. Recent regulations enforce strict data governance policies that have an elementary impact on the roles and responsibilities among peers in information management. Data governance becomes a strong need for data management in modern, regulation-driven conditions. Addressing GDPR compliance requires a coordinated strategy involving different organizational departments. Challenges still exist in this area with relatively little success of attempts to increase the span of data governance horizontally (across more functions) and vertically (across more business stakeholders). As information and data become an organic part of processes and activities - very collaborative, horizontal (cross-functional), and vertical (IT-business aligned), data governance processes need to be established (Delbaere & Ferreira, 2007).

This customer-related dimension is operationalized as Customer-Centric Orientation (CCO) in this research, and it is expected to be influential in the way how data governance impacts innovation and competitive advantage related dimensions of GDPR. In the initial phase of the data economy, there is increasing competition at the data service level. On top of this, regulators are insisting on data portability - and that makes a push for proven customer relationship strategies or customer-centric changing business models to help enterprises sustain and prevent customer loss (Rochet & Tirole, 2003). Customer-centricity is one of the models offered to generate profits for the long term, considering the sustainability that it provides with a focus on individual customer relationships as a means against various disruptive forces.

Research questions

The context above leads to the following *primary research question*: Can governance span be an organizational mechanism that leads to an increase in both innovation and efficiency in data compliance projects such as GDPR? There is an additional *supporting research question*: Can the relationship between this span and data compliance innovation be explained with a customer-centric orientation?

Research aim

Rather than in technology, the aim of the project is to look at data governance-related and marketing related organizational practices for empirical proof. The explored organizational practice mechanisms need to bring positive influences in both directions, innovation and efficiency, in exploration and exploitation, rather than either one of them - as outlined by Santa et al. (2011). EU companies could use GDPR regulation as a competitive advantage, where their associated benefits exceed their costs to comply. Effective data governance provides a means to obtain both utility from controlled data use, which is crucial in the current data economy, while at the same time ensuring proper safeguards and transparency of that control.

Furthermore, the research aims to prove that it is possible to tune multi-domain organizational practices in the back-end in order to cause desired effects in the two next-generation information management mandates at the front-end - data compliance and customer interaction management.

This research offers a ‘span of data governance’ as a management tool to increase both, at the same time - innovation in data compliance project and efficiency in privacy accountability in the same project. The research suggests this in the GDPR regulation case. An increase in innovation is achieved if customer-centric orientation is used as an active strategy alongside the data governance span.

1 Theoretical and practical contribution

1.1 Research Gap

Research on data governance is still in the early stages (Alhassan et al., 2016), while data governance is expected to be a leading pillar in embracing data management progress towards a more strategic space (as information aspects quickly outgrow the domain of information technology) (Kooper et al., 2011). Data governance effect on customer data compliance and customer data utility has not been empirically examined. In a literature review, no empirical research reports were found on any kind of relationship between data governance and compliance, neither any basic or complex theoretical models, including customer-centricity, innovation, and efficiency. There are no empirical studies available on any of the relations in the above-stated issues. Data governance is mainly intensive in defining activities; while implementing and monitoring challenges exist only in practice-oriented publications (Alhassan et al., 2018).

Data governance papers belong almost exclusively to the information system (IS) change management literature, and data governance programs follow primarily typical IS change management practice, extensively detailing just the technical aspects of IS changes and overseeing their organizational impact. The success or failure of such holistic IT projects has historically been ignoring the underlying organizational implications.

In the same way, there is a lack of view on data governance organizational impacts in a real business environment. Several studies and professional practitioners have already been warning over the years that there are too few companies with successful enterprise-wide information governance policies in place - which shows a real business-driven need to study the topic (Koulikoff-Souviron & Harrison, 2006).

An insufficient level of knowledge exists about data compliance and GDPR, and it is not clear what constitutes desirable project outcomes in this area. Uncertainty and inconclusive studies still exist generally about the relationship between organizational practices and compliance projects.

The article is part of the same broad quantitative research conducted by the same author (Vojvodic & Hitz, 2019), testing a longer list of hypotheses and relationships between variables. Variables were grouped based on their characteristics and split into different articles. This article extends the previous article by adding new variables Data Governance Span (DGS), Customer-Centric Orientation (CCO), Privacy Project Efficiency (PPE), and by investigating their relationships and impact on the overall model.

1.2 Practical contribution

The need for data governance to seriously assess aspects of business services such as regulatory compliance - has been hypothesized for some time. However, only recently has it become relevant in the wake of the global financial crisis and increased competitiveness. EU GDPR is a much-desired 'game-changer' for Europe's data economy and a compelling vision for what Europe's competitive edge can be (Duch-Brown et al., 2017). It is up to practitioners to set a high priority straightaway in their empirical responses on how EU companies can use this regulation as a competitive advantage, where their associated benefits exceed their costs to comply.

Enterprises often overspend on technologies and services in data gathering, mining, and processing in order to avoid risks of privacy debacles (Goldfarb & Tucker, 2011).

A GDPR project is a perfect catalyst or first step towards establishing a common data model for the customer and party data - that was pending and struggling in its aims to get organizational and line of business support, management attention, and funding for years. Extension of this party data model into an idea of building enterprise data as a service –

may fuel customer-facing functions operations and competitive advantage (Mantelero, 2016). Ideally, then, the compliance effort, if done right, should lead to better efficiency and innovative new business initiatives - which otherwise would never be funded. Data-driven innovations are becoming an increasingly vital feature of our societies, leading to growing data services dependence by individual consumers or economic subjects.

Data governance has been suggested as critical in obtaining utility from data use. Achieving adequate vertical strategies, combined as well with horizontal strategies, is a challenge for managers (Galbraith & Lawler, 1993; Porter, 1998), and this work contributes to categorization -followed by a clear action plan.

Existing data governance tools lack efficiency in several areas, including business alignment, measurement, data definitions, policies, and stewardship. There is a tendency to comment on data governance results and the potential or realized value from the perspective of such inefficient software tools. This research offers an understanding of some of the elements related to people, organizational design, and a culture that can help better evaluation.

All hypotheses of this study are organizational practice driven. A considerable amount of enterprise-wide information management concepts (seen as an immense investment and as a failure at the same time) - have been receiving attention as a technical concept mainly, lacking proper supplement on organizational practices (Silvola et al., 2011). This work goes further and offers multiple-domain organizational practices in the back-end (organizational design, go-to-market) - directly applied to the two next-generation information management mandates at the front-end, data compliance and customer interaction management.

1.3 Theoretical contribution

A major theoretical contribution of this work is practical and empirical inter-relation of several state-of-the-art business and research problem domains on the front-end while conducting integration of theories from microeconomics, organizational design, marketing in the back end. The field has weaknesses in the appropriate connections with causal variables, which led to this multi-variable exploration-driven quantitative research.

This article provides in-depth integration of the constructs relating to data governance, customer-centricity, leadership, efficiency, innovation within the research of the others. This broadens the application of each of the respective constructs.

Based on an extensive review of the previous literature, data governance is either placed narrowly and tactically (as a particular technology solution) or very broad - referring to the value of its strategic utilization and aligning with some high order and abstract concepts, such are corporate governance, IT governance or information governance. This work develops a framework that attempts to bridge these two places through the concept of governance span, thereby introducing a new interpretation of data governance.

Starting with the empirical linkage between two constructs and the establishment of the third construct as a potential mediator in between – is a practice that this research followed. Such an investigation is of interest to the field of organizational behaviour as it establishes the relationship of the third variable, offering many new relationships that have not been examined by earlier research.

The conceptual framework presented is based on three major grounding theories. The primary focus is the organizational theory of horizontal and vertical linking mechanism from Mintzberg (1979) and Galbraith (1974). The concept is incorporated into the data governance line of research and extended to examine two specific forms of impact - related to innovation development and project efficiency in a data compliance environment. The secondary focus was the intersection of the focal organizational theory with market orientation theory from Narver and Slater (1990) and Jaworski and Kohli (1993).

2 Theoretical background

This segment is organized according to the list of major constructs used in this quantitative research: Data Governance Span (DGS), Customer-Centric Orientation (CCO), Data Compliance Innovation (DCI) and Privacy Project Efficiency (PPE).

2.1 Data governance span

Data governance has rapidly gained in popularity (Khatri & Brown, 2010), where the term data is in the past years frequently being replaced by the term ‘information’ (Tallon et al., 2013). The origins of the information governance idea can be found in the 1990s in the work of Goodhue (1992), where it is related to the strategic planning of information resources. Information governance frameworks came two decades later from Brackett (2010) and Wende (2007). Data management starts entering the space of hierarchal higher-order constructs as progressing from low-level operations toward managerial functions. This can be seen through such overarching concepts like information governance (Kooper et al., 2011). For Korhonen et al. (2013), it is an organizational approach to both data and information management that formalizes a set of policies and procedures to encompass the full life cycle of data. Combining data and information in the definition is done by Plotkin (2013), where data governance is a system of decision rights and accountabilities for information-related processes. For Niemi and Laine (2016), information governance is even a strategically higher-order concept than IT governance.

Even on the data level, a similar movement of attributing governance as a wider span all-embracing concept - is seen. Data governance underpins all data integration, risk management, business intelligence, and master data management (Seiner, 2014). Consistent with that, Otto (2011) sees it as a companywide framework for assigning decision-related rights and duties to handle data as a company asset. There is a consensus among a group of scientists that perceive data governance as a means of extending the span of enterprise-wide decisions, rights, and responsibility. Weber et al. (2009) define this as the end-to-end distribution of decision rights and voting powers, responsibility acceptance and conflict resolution amongst stakeholders. Data governance raises a flag for a specified organization-wide decision-making framework that, according to Weill and Ross (2004), consists of tasks, responsibilities and roles. Moreover, accountability is essential to prevent errors and a lack of clear ownership of data management (Brackett, 2010). Data stewardship, as the operationalization of data governance (Plotkin, 2013), primarily needs to formalize accountability (McGilvray, 2008). Such clear objectives, tasks, roles and responsibilities for the whole span of governance - comes from establishing core (data) principles as a higher-order realm in any of the subdomains (Khatri & Brown, 2010). The data governance should extend its span vertically (more people) and horizontally (more processes, which naturally adds more people).

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Effective data governance provides values to traditional information management with expanding its span vertically - through alignment with business stakeholders, and horizontally – through cross-functional handling of data issues. Communication between departments (horizontal) and between management levels (vertical) improves the adaptability of data governance measures (Orr, 1998). As interpreted by Davenport and Short (1990) - the aim is to maximize interdependent activities that span across the company. One of the initial organization design innovations raised in the organization theory literature in the 1960s was ‘horizontal and vertical linking mechanisms’ (Mintzberg, 1979). Galbraith (1974) also introduced a continuum of horizontal mechanisms based on their increasing ability to handle information. Nadler and Tushmann (1988) proved that horizontal and vertical mechanisms can erase ‘firm's reporting regimes triggered’ drawbacks to cross-unit collaboration. This work argues that the two previously mentioned data governance processes need to be integrated to achieve the effective execution of a data governance strategy (vertically integrate and involve all business stakeholders, and horizontally integrate and involve a wide range of departments).

In order to understand the link between line-of-business participation and expansion of data governance span, more recent attention has focused on the framework of collaboration and knowledge transfer – as mandates of data governance on the top of information management. The root cause of challenges to engage business process owners is the lack of their comprehension in what their role really is in the project (Silvola et al., 2011). Therefore, every stakeholder needs to understand the relationships between business processes and data, and organizations must actively enforce this (Knolmayer & Röthlin, 2006) by setting up a data governance system that encourages collaboration between business and IT people (Dreibelbis et al., 2008).

It is already recognized as a continuous challenge that many information management initiatives just start and end within only one functional domain. They could be characterized by a lack of horizontal span. Data governance is able to address that challenge with its clear and unambiguous understanding of data, which is vital for the effective management of multidivisional companies (Hüner et al., 2011). Seiner (2014) highlights that data governance is a practical and effective initiative that serves well the promotion of data as a cross-organization asset. All functions need to provide a delegate, ensuring that usable data from that exact function are shared across (Krensky, 2014).

With the addition of cross-functional data governance teams, governance matures in its horizontal integration (Peterson et al., 2000; van Grembergen, 2004). Wende (2007) mentions fully governed data would mean that there are roles associated with critical data domains and for data elements that constitute such domains: data owner and or data steward are names used often for the roles. The need for data governance horizontally spanning teams is introduced as an organizational measure to extend the data governance span. It is rationalized as the team of data governance stewards (Seiner, 2014) that extends the span of governance vertically across operational data stakeholders and then horizontally across functions. A data governance steward is assigned individuals that communicate changes to data policy, regulations, and rules to their units or areas and that develop rules for handling data. Those that have some level of responsibility for the data they define produce and use during data entry, data integration and data analysis are usually named operational data stakeholders (Seiner, 2014). Line-of-business stakeholders that extend the vertical span of governance - belong to this group (De Leenheer et al., 2010).

2.2 Customer-centric orientation

Customer-centric orientation is adjusted construct derived from Shah et al. (2006) and Lamberti (2013) - and is the result of intersecting the customer-centricity concept with the integration concept. Lamberti (2013) summarized that the literature has generally agreed that customer-centricity finds a theoretical antecedent in the market orientation theory (Gummesson, 2008). Customer-centricity stresses more the nature of interaction with the customer, customer-centred processes and the individual customer intelligence (Ramani & Kumar, 2008; Shah et al., 2006). As opposed to customer-centricity, which is proactive, Bliss (2015) distinguishes ‘customer focus’ as efforts that are often highly reactive. High ‘customer satisfaction’ or superior ‘customer experience’ compared to customer-centricity are not transformational-scale movements as they do not force a change in behaviours (Kamakura et al., 2005). The customer-centric organization is often, in theory, in contrast with its opposite - the product-centred organization (Galbraith, 2005). As per Marsh (2010), looking into services that customers really need - is opposed to developing new products and persuading consumers to purchase them. Customer-centric firms favour having a decentralized organization that provides the possibility to change quickly and learn fast, adapting to dynamic customer needs (Kotler, 2003; Treacy & Wiersema, 1997).

Having all functional activities integrated and coordinated in delivering top-class customer value requires significant organizational change. Integration is a frequently used term in literature for operations that were not meant to operate together, achieving mutual success (Lawrence & Lorsch, 1967). For instance, Matthyssens and Johnston (2006) raise the need for a redesign of the traditional organizational structure and the formation of integrator roles between customer-oriented units. The integration of information brings more knowledge to be shared between all members, including sales forecasting, production plans, inventory levels, and promotion plans. Both academics and practitioners emphasize the relevance of internal integration and coordination as keys to developing customer-centricity. Gaur et al. (2011) proved a positive link between customer orientation and inter-functional coordination. Galbraith (2005) reports the need for a common goal shared across functions in order to implement customer-centred processes. Customer-centric marketing activities are cross-functional processes (O’Leary-Kelly & Flores, 2002). There is often poor coordination between sales and marketing, particularly in planning and goal setting (Kotler, 2003). They lack understanding, trust, co-operation and are in conflict (Achrol & Kotler, 1999). Their roles are culturally different - salespeople are intuitive, marketing people are creative (Cespedes, 1993).

The concept of customer data centrality, proposed by Syam et al. (2005), was empirically confirmed in the study of Lamberti (2013). Coordinating operations amongst interdependent parts of the organization brings customer insights from organization-wide communication if information integration processes are in place. Although in many cases, individual applications and lines of business are reasonably satisfied with the quality and scope of customer data that they manage, the lack of completeness, accuracy, and consistency of data across LOB prevents organizations from creating a complete, accurate, and up-to-date view of customers and their relationships (Berson & Dubov, 2011). Various information systems concepts are associated with the integration and consolidation of customers' data, such as customer relationship management (CRM), data warehouse (DW) and master data management (MDM). For Boulding et al. (2005), these functional customer-specialized systems provide pre-built functionalities for activities such as cross-selling, customized marketing communications or segmentation.

Customer centricity requires information integration to be complemented with a strategic direction change and implementation of appropriate organizational culture, structure, leadership, and measurement related practices (Shah et al., 2006). Fader (2012) notes that the significance of organizational culture in a customer-centric company assumes that individuals will strive to provide to every customer the quickest and most complete answer to any of his questions. In essence, leadership commitment is critical for both initiating as well as sustaining all initiatives for customer-centricity. Marsh (2010) claims that the effective placement of people who are in charge of the customer-centric initiative high on the hierarchical level - is a critical success factor in implementing a customer-centric strategy. Reinartz and Kumar (2003) argue that customer management-oriented organizations recognize the dynamic and importance of the evolving nature of the customer-firm relationship over time. The basis of this recognition is an understanding of metrics, such as customer lifetime duration, customer lifetime profit and the drivers behind them.

2.3 Data compliance innovation

The article is part of the same broad quantitative research conducted by the same author (Vojvodic & Hitz, 2019), testing a longer list of hypotheses and relationships between variables. Variables were grouped based on their characteristics and split into different articles. This article shares the Data Compliance Innovation variable with the previous article, but it extends the previous article by adding new variables Data Governance Span (DGS), Customer-Centric Orientation (CCO), Privacy Project Efficiency (PPE), and by investigating their relationships and impact on overall model.

Slater and Narver (1995) define the profitable innovation in superior customer value as market orientation highest priority. Likewise, Jaworski and Kohli (1993) argue that if the basis of market orientation is a code of doing something new. There is a large volume of published studies describing the role of creativity and innovation as key components of competitive advantage, and Im and Workman (2004) confirm this.

Innovations can scale from the core to peripheral, incremental to radical and architectural to disruptive innovations Gatignon et al. (2002). Boer and Gertsen (2003) support the idea of continuous innovation, which would consist of continuous improvement, learning, and innovation. Strategic innovation is a symbiotic union of strategy and innovation bodies of knowledge (Varadarajan & Jayachandran, 1999).

A considerable amount of literature has been published on the factors that influence the process to become more innovative: to appropriately configure processes, procedures, people, technologies and organizational setup (Boer & Gertsen, 2003), to have openness to innovation (Zaltman et al., 1973).

There are already authors that suggest measures for the degree of innovation: measurement of the innovation capacity in the enterprise (Cordero, 1990); the degree of newness of the product under development (Sarin & McDermott, 2003); innovation capacity or capability for knowledge and technology management, idea management, project development, and commercialization (Doroodian et al., 2014).

GDPR opens a new interaction channel with customers (the process of getting consent or a self-service portal for requesting review or removal of customer data). It is possible to use that channel not simply to request and respond to what is demanded by regulation but to enrich this purpose. The channel can be used in innovative ways to add value to customer engagement and to act on customer behaviours in order to drive trust, loyalty and even new services. Firms can achieve a higher level of insight into their customers' needs by using data compliance interaction opportunity (Sawhney et al., 2005).

The decrease in the cost of storing data has made it possible to capture, save, and analyse a much larger amount of information about individuals, consumers, and customers, as listed by Acquisti (2010). Innovation and improvement of services and products are facilitated by observing customer activity so precisely. Organizations also can monetize these data as behavioural data generated on the platform (Tallon, 2013).

Determining which datasets a company should monetize or acquire is on its own complex decision. It is necessary to place in front of customers a platform for agreements between data holders and data subjects in order to optimize privacy trade-offs and selectively protect or disclose different types of personal information (Acquisti et al., 2013).

The way to take advantage of the personal data concerns and regulators activity is to utilize these exchange data in order to add value for customers. Álvares-Bermejo et al. (2016) and Myles (2015) claim that making data, permissions, and control access to customers will support a trusted relationship where customers intentionally share more of their data for added value or personalized offers and for other benefits. Granularity in customer data categorization and attribution leads to innovation, services, and ideas on how to make the customer happier. Organizations can improve the customer experience by monitored attributes on how a customer wants to be engaged in actions (Bolognini & Bistolfi, 2017; Braun & Garriga, 2018; Kasabov & Warlow, 2010).

By adding more value to the usually minimalistic data request, enriching these data on the fly and with innovation in the dialogue between consumers and organization, it is possible to adopt a customer-centric engagement model combined with compliance-driven undertakings (Kumar et al., 2010). This is particularly true with openness and proactivity with customers in terms of them knowing how their data is used and how they are benefitting from the use of their data. Such engagement and interaction give the opportunity that each buyer journey should be handled uniquely, with analysis of the multiple data collection sources to properly and successfully segment customers based on browsing behaviour (Kunz et al., 2017). Ramani and Kumar (2008) suggest that the technological progress has resulted in increasing opportunities for interactions between firms and customers for those who will take advantage of information obtained from these successive interactions in order to achieve profitable customer relationships.

Gregory and Bentall (2012) argue that systematically classifying customer processes provides a collection of customer data that show the most popular process routes, from the starting point of acting to the end-point of need satisfaction. Such data can also help firms to identify potential gaps in markets and demand for products and services that do not exist (Moormann & Palvolgyi, 2013).

2.3 Privacy project efficiency

Operational efficiency refers to leading and controlling, measuring and improving the processes with eventual process performance gains (Santa et al., 2011). The firm will outperform competitors if core processes have eliminated waste, reduced costs, in addition to adopting appropriate technology innovation (Porter, 1998). In modern times, the objective of being flexible and the ability to quickly adjust to changes raises the importance of operational efficiency (Slack et al., 2013). Some of the operational efficiency movements are replaced by different enterprise information systems initiatives (Davenport & Short, 1990).

Project efficiency is predominantly used to measure project success, meaning fulfilment on schedule, with agreed costs and quality (Berssaneti & Carvalho, 2015; Srivannaboon & Milosevic, 2006). The project was believed to be successful when the predicted schedule was met (Atkinson, 1999). Pinto et al. (2009) describe the efficiency of the implementation process as a measure of the performance of the project team and if they completed the project on schedule and on budget. Time-based project performance becomes vital to the competitiveness of an organization (Droge et al., 2004; Scott-Young & Samson, 2009). Regardless of so much focus on the time dimension, too often, projects experience costly delays in completion ((Belassi & Tukel, 1996; Leung et al., 2002). Project escalations are, in most cases, related to the risk of not fulfilling the project on time (Iyer & Jha, 2006).

Data governance is related to project management. In its project monitoring, data governance requires an implementation plan that follows a well-defined and proven methodology (Berson & Dubov, 2011). Customer privacy protection is one of the data governance-driven projects that require efficiency in GDPR data compliance. Accountability is distributed across operational data stakeholders in all functions, including business process owners - by appropriate technical and organizational measures that enterprises can use to demonstrate compliance with personal data protection. At the heart of such implementation was a data governance program of reconciliation of sensitive data by identifying any gaps or overlaps in their lifecycle, missing necessary responsibilities assigned to process owners within line-of-business or to other operational data stakeholders. Charlesworth and Pearson (2013) conclude that then for organizations - privacy involves the application of laws, policies, standards, and processes via which personal data is managed. Organizations extend such accountability with responsibility and hold employees accountable for any misuse of that information (Charlesworth & Pearson, 2013; Weber et al., 2009).

Data governance is linked to control and accountability, mainly in the management control systems literature (Otley & Berry, 1980). Data, seeing data or updating data comes with responsibility. The framework, workflow, and process capabilities aim to extend the scope of data governance to more data and to more people – to achieve accountability within the organization (De Leenheer et al., 2010). Policy enforcement is a data governance term for a technical measure for developing accountability attached to data and that follows and ‘travels’ with that data (Pearson & Casassa-Mont, 2011). A history of data manipulations and inferences can be maintained and checked against a set of policies that are supposed to govern them, that way providing mentioned accountability (Charlesworth & Pearson, 2013).

A number of authors have covered the process of data governance reconciliation accountability across the enterprise. Fatema et al. (2017) describe that in a data governance-driven lifecycle of personal data, first consent is generated, then business processes for personalized services collect personal data and classify them accurately to provide protection of sensitive personal data. This is to be managed in a way that compliance with the legal requirements can be verified (transformation for isolation of sensitive information, ensure anonymity, demonstrate traceability). Data are then produced following proper business rules, entered into the system in a timely manner, and appropriate roles are notified about updates – if everyone involved is held accountable in this process (Seiner, 2014).

3 Research model

3.1 Conceptual framework

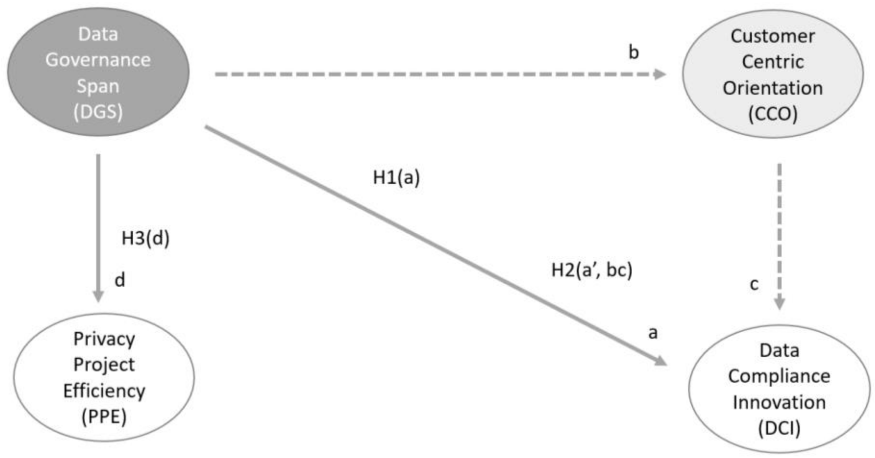
The argumentation provided in the theoretical background section leads to the hypotheses listed below.

H1: Data Governance Span (DGS) leads to an increase in Data Compliance Innovation (DCI).

H2: There is a mediating effect of Customer-Centric Orientation (CCO) on the Data Governance Span (DGS) – Data Compliance Innovation (DCI) relationship.

H3: Data Governance Span (DGS) leads to an increase in Privacy Project Efficiency (PPE).

Figure 1 | The primary hypotheses research model



Source: authors

3.2 Construct conceptualization

This research went through the process of construct conceptualization and re-conceptualization for all of its variables. To develop the constructs, the guidelines of Diamantopoulos and Winklhofer (2001) are followed. A construct can be too broad and must be narrowed so that they can match model outcomes with their estimated loadings (Wright et al., 2012). The research used theoretical integration for the majority of constructs. Hagger and Chatzisarantis (2009) outline that theoretical integration removes gaps in theories, decreases redundancy and supports identifying the most important variables to manipulate. Some constructs can fill explanatory gaps in the others, eliminating unnecessary variables between theories (Wright et al., 2012).

With the aim to minimize the coverage of any concepts outside of the focal construct domain, construct items were generated and assembled (Churchill, 1979). This research used both inductive and deductive methods in construct and item development (Hunt, 2016; Schwab, 1980). A necessary prerequisite for new measures is a clear link between items and their theoretical domain provided in the theoretical background part of the project (Hinkin, 1995).

The constructs research models are reflective (Bollen & Lennox, 1991; Jarvis et al., 2003). No construct is defined as the result of, and/or the cause of, some other construct. The theme that ties the exemplars together is strongly underlined in the theoretical background (Summers, 2001).

This research suggests data governance span (DGS) consists of vertical (business stakeholders' span) and horizontal (cross-functional span), and that formal engagement which assumes line-of-business stakeholder participation responsibility and formulation of objectives, evaluation of results and use of output are related to the former, while the share of information and ideas between functions and cross-functional communication to resolve data issues is related to the latter one.

Customer-centric orientation (CCO) is an adjusted concept and a result of intersecting the customer-centricity concept with the integration concept, which now consists of three subconcepts: organizational integration (combined from internal integration and organizational realignment), information integration (combined from interactive customer relationship management and systems and process support), and strategic customer-centric direction (includes revised financial metrics and leadership commitment). External integration and customer integration were not relevant to the context of this research.

The innovation part of the concept of data compliance (DCI) is based on the integration of innovation and market orientation theories related to customer engagement. The concept of customer interaction can be integrated with market orientation focused innovation. This can be applied in the setup of data compliance with GDPR as an example, as regulation opens new communication channels that can be used in innovative ways to add value to customer engagement and interaction.

Privacy project efficiency (PPE) integrates the concept of operational efficiency with the concept of project management in order to justify project efficiency as a concept used in this research. Establishment accountability for customer privacy protection is one of the data governance-driven projects that require efficiency. Accountability was distributed across operational data stakeholders in all functions, including business owners. Accountability is derived from the concept of control with the integrated GDPR accountability principle. This mandates organizations to implement appropriate technical and organizational measures to be able to demonstrate their compliance.

3.3 Hypotheses

H1: Data Governance Span (DGS) --> Data Compliance Innovation (DCI)

Data governance is used to increase innovation associated with customers data. A tier of governance driven data explanations is ideal as a central platform for studying and repurposing the data (De Leenheer et al., 2010), as this is a prerequisite for innovation. Greater data utility comes from higher usability and a wider span of data. Traceability of customer data improves further usability across segments, especially for customer-centric units. King and Forder (2016) add that this generates new ideas and innovation on revenue-generating customer engagement.

A prerequisite for this is data governance processes with a vertical and horizontal span that help to discover and resolve inconsistencies and incompleteness caused by different business units. Data attributes that describe business entities often contain different values for the same attributes across different applications and lines of business - impacting the ability to identify relations between business entities (for example, accounts and payments, customers and households, and products and suppliers) (Berson & Dubov, 2011).

As a source of creativity, the exchange of information between people, people and information systems between disparate information groups is extremely inefficient due to gaps in whereabouts, meaning, usage or quality of non-governed data. Some of the reasons are discrepancies brought by technology maturation, natural language application discourse, legacy systems with application-specific context (Weber et al., 2009).

For innovative decisions from business owners on the top of data, it is necessary to trust in the information system underneath. The data governance tier ensures higher user engagement leading to data being shared more across departments and data domains. Organizations with governed data state higher accessibility of data. Data governance becomes a driver of increased information flows within the organization (De Leenheer et al., 2010). This increase in appreciation translates into an increase in the use, leading to innovation.

Trust in the system needs to be supported with good data quality, ensured by data governance (Otto, 2011) - to make better and more accurate decisions on marketing strategy, compelling product, customer's behaviour, propensity to buy (Seiner, 2014). Information can be gathered from customers, and then also needs internal well-governed information processing capabilities in order to channel externally collected information to the most appropriate internal stakeholders – to trigger innovative ideas.

Communication brings creativity and innovation, and horizontal integration is encouraging communication between different functions (Gatignon & Xuereb, 1997). Montoya-Weiss et al. (2001) claim that this increases the amount of information flow in the organization. Ford and Randolph (2016) note that it connects resources and skills from different functions, enhancing the utilization of organizational resources.

Tidd (2001) stated that horizontally spanning teams have more mechanisms for bridging boundaries to create innovative solutions within organizations - as team members are able to develop a shared language and shared mental models. This makes it easier to identify problem areas early in the enterprise-wide process and find solutions that are shared by the team members in the same language (Santa et al., 2011). In horizontally integrated teams, people tend to reach further and faster to gain or spread knowledge (Robbins, 2003).

Balanced, comprehensive, and cross-functional planning influences innovation (Downs & Mohr, 1976), and high participation in making decisions increases involvement and the commitment to innovate (Damanpour, 1991). It boosts information flow and communication up and down and rise innovation (Kanter, 1983), supports collaboration that encourages new ideas and risk-taking as fear lessens (Pierce & Delbecq, 1977), integrates problem-solving that inspires innovation (Clark et al., 1987), and provides horizontally integrated perspective sharing that also supports innovation (Clark et al., 1987).

H2: Mediating role of Customer-Centric Orientation (CCO)

The general aim to retain and serve well existing customers cultivates hesitancy to challenge the status quo, and it is not enough to generate innovation (Johne, 1994). An organization must also identify new products and services to offer before existing customers even think of them (Prahalad, 2016).

The project of transformation to a customer-centric model, with necessary changes in business processes, requires an understanding of the data lifecycle, as well as increased trust in the data. Operating within the customer-centric model requires ad hoc, trustworthy, relevant, consistent and timely information about customers.

Jaworski and Kohli (1993) and Day (1994) argue that market orientation delivers strong norms for sharing information and reaching a consensus of meanings with functionally coordinated actions of customer-facing units engaged at the realization of competitive advantage. Imai et al. (1985) claim that market intelligence, with external orientation and communication, networks, and involvement with suppliers and customers, facilitates innovation.

Krinsky and Jenkins (1997) recommend that representatives from R&D, sales, marketing, finance, and other key functions could be given a central role in developing strategies. Activists, representatives from different organizational functions, young people, newcomers, or people at the organizational periphery are the ones that fabricate innovation (Floyd, 1992). Integrative organizational structures of customer-centric models clarify interdependencies and build information processing capabilities and eliminate cross-departmental data translations. Inter-functional coordination and the integration of diverse customer-centric units in the organizational matrix might have integrator roles or other authority giving focus on back-end units to a particular customer. Such design improves assessment for enterprise-wide impacts of data-related decisions and leads to the start of a useful impact analysis where the enterprise data issues are seen as cross-functional (Smart & Whiting, 2001).

As a customer-centric dimension, information integration allows an organization to understand the customers' goals, demands, abilities, and their propensity to request additional products and services, thus increasing the innovative cross-sell and up-sell revenue opportunities and offer a rich set of personalized services (Berson & Dubov, 2011). For most customer-oriented units, the ability to deliver the right personalized content cross-device and cross-channel is the most favoured segment of the process that builds value-added innovative customer engagements. The requirement for content-channel mapping is traceable, authoritative and governed data (Buckley et al., 2014; Moormann & Palvolgyi, 2013). Komssi et al. (2015) argue that assembling well-functioning innovation and consultative selling customer-centric teams - leads to greater leverage in the existing knowledge of the data about customers that lies within its line of business and integrates this knowledge.

Jaworski and Kohli (1993) identified that the collection, storage and analysis of market intelligence across all departments - boost collaboration and innovation. Lukas and Ferrel (2000) found that market orientation, with the customer-centricity concept, has a positive relationship with the development of new products and services and is directly increased by inter-functional coordination.

Hence, the summary of this section could conceivably be a hypothesis that Customer-Centric Orientation (CCO) is mediating the relationship between Data Governance Span (DGS) and Data Compliance Innovation (DCI).

H3: Data Governance Span (DGS) --> Privacy Project Efficiency (PPE)

GDPR regulation required multi-source data discovery at its inception, including a data privacy accountability reconciliation project. There are various options for assigning data privacy accountability a subset of the data from the enterprise perspective to the operational data stakeholders. One of them is through data governance-approved policy, making business owners become accountable for how data in their domain are managed (Seiner, 2014). If the policy is designed by a data governance stewardship team, having the enterprise perspective of all functions in its domain, this is an effective and quick way for the enterprise-wide spread of accountability.

Data governance enables the organization to manage its data as a corporate asset while requiring individual accountability for specific roles (Harris, 2011). Switching responsibilities and accountability from one person to another is enabled in data governance frameworks (Silvola et al., 2011). Seiner (2014) outlines that there are often changes in specifications on how data are to be defined, produced and used given by an external regulating authority or internal business practice.

Accountability adds business stakeholders as information and data owners involve them in customer data related interactions and require their participation and iterations (Breaux & Alspaugh, 2011).

Feurer et al. (2000) add to this that the project is more efficient, and the resource support process is leaner if line-of-businesses work closely with the project team. Müller and Jugdev (2012) declare that insufficient operational efficiency of information systems is generally caused by the absence of a user or business manager participation. They can provide valuable input such as fresh ideas, feedback on the performance of existing systems, as well as insight on gaps in information systems. This is increasing the efficiency of the project, as unacceptable or unimportant flows are eliminated at the start (Robey & Farrow, 1982). Such business users and managers' collaboration with the project team and during the goal-setting process is evidenced as a factor that reduces project cycle time (Müller & Jugdev, 2012).

Horizontal integration from a data governance concept can be related to project efficiency. Horizontally well-integrated teams are shortening cycle times (Griffin, 1997). Immediate stakeholder input are factors in the contribution of cross-functional integration projects success (Brown, 1997; Brown & Eisenhardt, 1995). Correspondingly, the horizontally integrated data governance team decreases the probability of unnecessary re-work, and that way speeds up the project implementation (Rulke & Galaskiewicz, 2000). Data governance business semantics can help in the evaluation of regulatory compliance of services if it is validated by relevant and trusted people from very different business functions, including legal and compliance departments (De Leenheer et al., 2010). The speed of the project is increased as trust reduces the agreement making the process and simplifying the content of agreements (Bibb & Kourdi, 2004). Problem-solving is improved with assembling the knowledge base from different units (Lampel, 2001). High levels of team problem-solving and quick troubleshooting are positively related to faster project execution.

Data governance adds to information management with the advanced application of the measure. Kueng (2000) highlights the relevance of implementing measures of business processes, leading to its efficiency, including the whole project. Improving operational effectiveness involves determining key performance objectives and establishing benchmarks. The data governance framework is based on iterations which bring efficiency. Data governance brought a practical shift of understanding that it is not just about data, rather is the recurrent communication of process owners and those who enter the data into information systems (Vilminko-Heikkinen & Pekkola, 2013).

The arguments provided in this section lead us to the eventual assumption that it is likely that Data Governance Span (DGS) leads to an increase in Privacy Project Efficiency (PPE).

4 Research methods

To establish awareness and relevance of the research problem, a literature search was first conducted. Looking into potential causal relations between different concepts from processed body-of-knowledge, over time, the integration of different concepts was used for selected for final variables.

Identified databases and database centres accessible from the University Library that are relevant to the dissertation topics: ProQuest, EBSCO, Lexis Nexis, NBER Papers, Journal Storage – JSTOR. Search engines: Semantic Scholar, Scopus, Web of Science. Some of the articles not available in the database were obtained directly from authors.

A literature review was complemented with the identification of other important/relevant information sources, namely web pages/servers of leading consulting companies, analyst companies, discussion groups, and professional organizations.

A quantitative method was selected with the online survey as a data collector. Used survey on the completely protected anonymity and minimized the risk of the bias due to organizational sensitivity of data governance and compliance topics. Quantitative research methods are also used as the aim was to provide a relatively conclusive answer to the research questions.

Data analysis, processing, and hypotheses testing were performed with the structural equation modelling (SEM) partial least square (PLS) statistical method using the SmartPLS tool.

PLS offers accurate predication capability (Fornell & Larcker, 1981). Such predictive direction was used here to anticipate inter-relations of data governance, innovation, efficiency, leadership and customer-centricity in the model. PLS generally requires a smaller sample size to validate models than other SEM techniques. PLS is a suitable method when the research subject being investigated is relatively new and still in development (Chin, 1998). The field of information systems (IS) is strongly associated with the use of the partial least squares (PLS) technique (Chin, 1998).

As opposed to the covariance-based SEM (requires already a strong prior theory and sizeable sample (e.g. > = 300)) - variance-based SEM is dedicated to theory exploration rather than confirmation and does not necessarily entails strong prior theories and established operationalizations, it supports small sample, e.g. < 100, it does support constructs with single-item, supports data sets with missing values as well as data sets with multicollinearity. PLS distributional assumptions are flexible, which in turn could result in more reliable findings (Gefen et al., 2000).

4.1 Operationalization and measurement instrument creation

The survey is developed by balancing literature and fieldwork. To avoid scale proliferation, when possible, existing scales were consulted (Bruner, 2003). The scales had to be adapted due to change in construct generalization hierarchy, and the reassignment of different content areas to the construct and amount of items had to be dropped (Finn & Kayande, 1997).

As suggested by (Robinson et al., 1991), the first step in scale construction was writing the items to be included in the scale based on the literature review. The resulting items were then reduced and refined through discussion between the author and experts in order to select items most closely related to the definition of the construct and to eliminate closely related items.

In developing the measures, mentioned adaptation to the focal concepts of this research while maintaining original concepts (Manager Involvement (Vanlommel & De Brabander, 1975), Cross-Functional Integration (Enz & Lambert, 2015), Internal Integration (Swink & Schoenherr, 2015), Information Management (Goodhue et al., 1992), Customer Centricity (Marsh, 2010), Project Internal Efficiency ((Pinto & Mantel, 1990) and (Pinto et al., 1993). Degree of Innovation (Sarin & McDermott, 2003) and Interaction Orientation - Interaction Response Capacity (Ramani & Kumar, 2008). It is argued that the constructs used in this research are special cases of some other constructs and thus sharing many key behavioural characteristics with these overarching concepts while at the same time having some element of 'newness'. The existing constructs were incorporated in the body of knowledge focal constructs, and therefore of, the various insights from the literature from both sides were integrated.

This study argues that PPE is a special case of Project Internal Efficiency as they share many key behavioural characteristics with these overarching concepts while having some elements unique to data governance span related vertically integrated business users and their participation, and cross-functional integration as well as GDPR privacy accountability related internal project efficiency.

On the other hand, the work assumes that the integration of subsets of constructs of Manager Involvement and Cross-Functional Integration can produce a Data Governance Span, as well as the integration of Customer Centricity, Information Management, and Internal Integration can serve the same purpose for CCO, while Degree of Innovation and Interaction Orientation integrated to form a question for DCI.

Five-point Likert-type scales were used (e.g., 1=strongly disagree to 5=strongly agree) and consistent with standard practice, ordinal data has been treated as continuous data in order to facilitate interpretation (Flora & Curran, 2004). It is important that the scale used generates sufficient variance among respondents for subsequent statistical analysis, and this is the case with the Likert scale (Hinkin, 1995).

Once the survey items were determined, the procedures suggested by Dillman (2007) for survey design were employed. The instrument was being developed with parallel consultation with subject matter experts with significant project experience from academic and from professional consulting practice. The next step was a pre-test of 30 participants in total to check the overall validation of the proposed model. The pilot test evaluated the Cronbach Alpha and Exploratory Factor Analysis. Also, there were no outliers found during the pre-test. The cross-sectional construct reliability and validity were tested by SmartPLS. In terms of AVE, the results pass the required minimum of 0.5 (Chin, 1998). The reliability of the constructs was confirmed (Thorndike, 1995).

4.2 Data collection

The survey was hosted using the SurveyMonkey online survey application (www.surveymonkey.com. The first page served as well as a tutorial page where prior to answering the questions, participants were required to read and agree to a consent form describing the purpose of the research, the procedure involved, confidentiality, and researcher contact information.

Participants for the full study research were recruited directly by the author. They were contacted via email or via LinkedIn messages. The research topic is very compelling to the targeted roles, and many of them express interest in receiving the research results.

Data collection was administrated during December 2018. 147 responses were collected, from which 98 were completed. Thus, the completion rate is 66%. The size of the research pool was calculated at the end of data collection, and 565 contacted target profiles were recorded, which gives the competition rate of 26%. This would account for around 25% of the entire target profile population (565 out of around 2000). Control parameters were defined for country and industry, and within these sampling parameters, the random sampling has conducted the generalizability of the study (Newsted et al., 1998).

4.3 Sample and sample size

Generalization of the results is supported by the fact that GDPR regulation is harmonized law and does not vary across countries, as well as that there are a limited amount of targeted roles and target companies in Europe.

There were two major criteria involved in selecting what qualifies in the definition of 'the observed firm'. These are enterprises that process data about customers and have data governance teams. The industry field was also used as a filter in the search function on LinkedIn. Data governance teams are set in organizations of bigger size, those that process a larger amount of data. This is a list of industries that were prioritized as those that fill the criteria: Financial Services, Telecommunications, Aerospace or Transportation, E-Commerce or Retail, Technology, Software or Internet, Consulting, Healthcare. These industries cover business-to-consumer areas.

Responses are asked from senior members associated with data management, data governance or compliance teams (internal leaders or external partners/consultants). Internal leaders have roles of data governance heads, leaders, managers, directors and are easy to identify on LinkedIn using search per key words in the title. External partners and consultant titles are data governance consultants, advisors or heads of data governance practice. They, in many cases, belong to the four biggest consulting companies (Deloitte, Ernst & Young, KPMG and PricewaterhouseCoopers) or some of enterprise software vendor (Oracle, IBM, SAP). They are considered as ‘high profiles’ and on senior management positions, not taking time to fill online surveys. This triggered the decision on minimization of survey questions in order to ensure collecting a sufficient number of answers from the right people.

We can conclude that the sample was drawn 2000 of target companies as a query on LinkedIn shows the existence of around 2000 target profiles in desired regions and desired industries. Firms were initially randomly selected from the list of companies in each control variable category (region and industry).

The “10-times rule” method is the most broadly used minimum sample size estimation method in PLS-SEM (Hair et al., 2017). The dependent construct with the most independent variables is Data Compliance Innovation (DCI) (2 paths leading to knowledge sharing). Thus, 20 is the minimum required sample size according to this rule.

The simplicity of application contributed to the popularity of the 10-times rule method’s. Nevertheless, it has been shown in the past to lead to inaccurate estimates (Goodhue et al., 2012), and its minimum sample size estimation does not depend on the magnitude of the path coefficients in the model (Kock & Hadaya, 2018). There are other recommendations related to item-to-response ratios range from 1:4 (Rummel, 1970) to at least 1: 10 (Schwab, 1980) for each set of scales to be factor analysed.

5 Results and discussion

5.1 Demographics of respondents results and discussion

Aerospace or Transportation (AT) scored the highest across all variables apart of DCI. AT, although represented by a small number of companies, seems to have a high rate of data governance span, driven by the leadership of governance teams and impacting efficiency in data compliance project, but not innovation (2.50 compared to all-industries-average of 3.00).

CO scored the lowest across all variables. Consulting companies, although advising all others to do so, do not use data governance frameworks as extensively as their customers.

E-Commerce and Retail (ER) is the second highest on DGS and highest on DCI. This industry is highly focused on innovation in data regulation (3.50 compared to all industries average of 3.00) and extensively uses data governance span but does not obtain the same results in project efficiency (2.50 compared to all-regions-average of 3.09).

Technology, Software or Internet companies (TSI) do not have vertical integration in data governance frameworks, especially in the formulation of objectives, evaluation of results and use of outputs (DGS2 is 3.17 compared to the all-industries-average of 3.66).

The telecommunication industry (TC) was having lower efficiency in data compliance project (2.40 compared to all industries average of 3.09).

Firms in Central and Eastern Europe (CEE) did not use innovation enough in data compliance. DCI is the lowest in the CEE region (3.25 compared to all-regions-average of 3.44, 2.85 compared to all-regions-average of 3.00). DGS1 is the second lowest in CEE compared to all-regions-average (3.75 and 3.15, respectively). DGS1 refers to the business stakeholder involvement in the formal engagement, which assumes their responsibility (identify data to be governed, rules, policies, follow-up).

Southern Europe (SE) firms have the highest cross-functional integration and horizontal data governance span.

Western Europe (WE) companies have the highest level of customer-centricity, especially related to information integration and strategic direction. However, their overall data governance span is the lowest, having both horizontal and vertically integration lowest compared to others

Table 1 | Means of regions

	Avg of DGS1	Avg of DGS2	Avg of DGS3	Avg of DGS4	Avg of CC1	Avg of CC2	Avg of CC3	Avg of PPE1	Avg of DCI1
CEE	3.75	3.70	3.55	3.80	3.45	3.25	3.35	3.25	2.85
OEU	4.25	4.25	3.75	3.75	3.38	3.25	3.38	3.13	3.00
SE	3.95	3.67	3.81	4.00	3.52	3.33	3.43	3.14	3.05
WE	3.71	3.55	3.51	3.59	3.33	3.76	3.63	3.00	3.04
ALL	3.82	3.66	3.60	3.73	3.40	3.52	3.51	3.09	3.00

Source: authors

Table 2 | Means of industries

Row Labels	Avg of DGS1	Avg of DGS2	Avg of DGS3	Avg of DGS4	Avg of CC1	Avg of CC2	Avg of CC3	Avg of PPE1	Avg of DCI1
AT	4.25	4.25	4.25	4.00	3.50	3.50	3.50	3.50	2.50
CO	3.00	3.00	3.00	3.20	2.80	3.20	3.00	2.40	2.40
ER	4.00	4.00	3.50	3.75	3.25	3.25	3.75	2.50	3.50
FS	3.90	3.71	3.71	3.84	3.43	3.55	3.63	3.24	3.08
HC	3.70	3.90	3.10	3.30	4.00	3.60	3.60	3.20	2.70
OT	3.67	3.67	3.83	3.83	2.67	3.83	2.83	3.17	2.67
TC	4.00	3.75	3.50	3.63	3.38	3.38	3.25	2.63	3.00
TSI	3.67	3.17	3.58	3.83	3.42	3.50	3.58	3.00	3.33
ALL	3.82	3.66	3.60	3.73	3.40	3.52	3.51	3.09	3.00

Source: authors

5.2 Descriptive Statistics

The minimum item value on the Likert scale is 1, while the maximum value is 5. The range between the minimum and maximum values of mean statistics is 0.816, while it is 0.908 for standard deviation. The values are wider spread around the mean.

In the DGS construct, respondents reflected that formal engagement, which assumes business users responsibility and cross-functional communication to resolve data issues, have stronger levels (73.5% and 73.5%, the highest level of agree and strongly agree answers).

Respondents are of the opinion that customer-focused functional teams work better together compared to the level of supported customer data being integrated, consolidated and used for analysis or level of usage of strategies with customer metrics (73.5% average portion of agree and strongly agree with answers versus 61.2% and 61.2%).

Data compliance innovation and privacy project efficiency were seen in the eyes of respondents with notably weaker levels compared with governance span and customer-centricity. With 69.7% and 65.3% versus 38.7% and 38.7%. Innovation in data compliance project is still having less negative ratings. The highest portion of disagreeing and strongly disagree answers is 31.7% in PPI (privacy project efficiency).

Table 3 | Descriptive Statistic Results

	No.	Missing	Mean	Median	Min	Max	St.Deviation	Excess Kurtosis	Skewness
DGS1	13	0	3.816	4	1	5	0.983	0.317	-0.864
DGS2	14	0	3.663	4	1	5	0.999	-0.497	-0.585
DGS3	15	0	3.602	4	1	5	0.956	-0.41	-0.546
DGS4	16	0	3.735	4	1	5	0.91	0.292	-0.848
CC1	19	0	3.398	4	1	5	1.018	-0.371	-0.456
CC2	20	0	3.52	4	1	5	1.099	-0.951	-0.263
CC3	21	0	3.51	4	1	5	0.982	-0.142	-0.653
PPE1	22	0	3.092	3	1	5	1.06	-0.583	-0.238
DCI1	23	0	3	3	1	5	1.107	-0.945	-0.046

Source: authors

Table 4 | Rating per indicator

	DGS1	DGS2	DGS3	DGS4	CC1	CC2	CC3	PPE1	DCI1
Strongly agree	23	18	14	15	11	21	11	7	7
Agree	49	48	49	57	41	33	49	31	31
Neutral	13	14	18	12	26	22	20	32	23
Disagree	11	17	16	13	16	20	15	20	29
Strongly disagree	2	1	1	1	4	2	3	8	8

Source: authors

5.3 Hypothesis testing

To test the hypotheses, partial least squares (PLS) in SmartPLS is used.

Paths connecting two latent variables represented hypotheses in the structural model. Paths in SEM PLS are standardized regression coefficient gives us a mixture of a (causal) effect and the distribution of a variable (Hair et al., 2017). Path weights, therefore, vary from -1 to +1. The path coefficient value needs to be at least 0.1 to account for a certain impact within the model (Wetzels et al., 2009). In SmartPLS, in order to test the significant level, t-statistics for all paths are generated using the SmartPLS bootstrapping function (Kushary, 2000).

From the obtained results:

Data Governance Span (DGS) influence positively Data Compliance Innovation (DCI) (β(a)=0.378, t=4.143, p=0), therefore, Data Governance Span (DGS) leads to an increase of Data Compliance Innovation (DCI), and the H1 hypothesis is supported.

Data Governance Span (DGS) influence positively Privacy Project Efficiency (PPE) (β(d)=0.502, t=6.125, p=0, therefore, Data Governance Span (DGS) leads to an increase of Privacy Project Efficiency (PPE), and the H3 hypothesis is supported.

According to (Baron & Kenny, 1986), full mediation is proven if:

From the analysis, both new relationships, independent variable to mediator variable and mediator variable to dependent variable, must show significant impact after running bootstrapping procedure (condition 1).

The introduction of the mediating variable should reduce the coefficient value between independent to dependent variable compared to the previous model without a mediator, and the new value is not significant (condition 2).

After running the bootstrapping procedure, the total indirect effect of the independent variable – mediator variable – dependant should be significant (condition 3).

Finally, the effect of both mediating effects also is tested in the posthoc analysis.

From the obtained results:

Customer-Centric Orientation (CCO) is identified to influence Data Compliance Innovation (DCI) positively (β(c)=0.286, t=7.418) and has been influenced positively by Data Governance Span (DGS) (β(b)=0.473, t=4.418) (condition 1 fulfilled). The introduction of the mediating variable reduces the coefficient value between Data Governance Span (DGS) – Data Compliance Innovation (DCI) relationship from β(a)=0.330 to β(a')=0.194, and a' is not significant (t=1.443) (condition 2 fulfilled). Total indirect effect of Data Governance Span (DGS) - Customer-Centric Orientation (CCO) - Data Compliance Innovation (DCI) relationship is significant (β(bc)=0.135, t=2.213) (condition 3 fulfilled). Therefore, there is the full mediating effect of Customer-Centric Orientation (CCO), and it is the underlying mechanism of the relationship on Data Governance Span (DGS) - Data Compliance Innovation (DCI), and H2 is supported.

Table 5 | Hypotheses testing results

Hypothesis	**Result**
H1: Data Governance Span (DGS) leads to an increase in Data Compliance Innovation (DCI)	Supported
H2: There is the mediating effect of Customer-Centric Orientation (CCO) on the Data Governance Span (DGS) – Data Compliance Innovation (DCI) relationship.	Supported
H3: Data Governance Span (DGS) leads to increase in Privacy Project Efficiency (PPE)	Supported

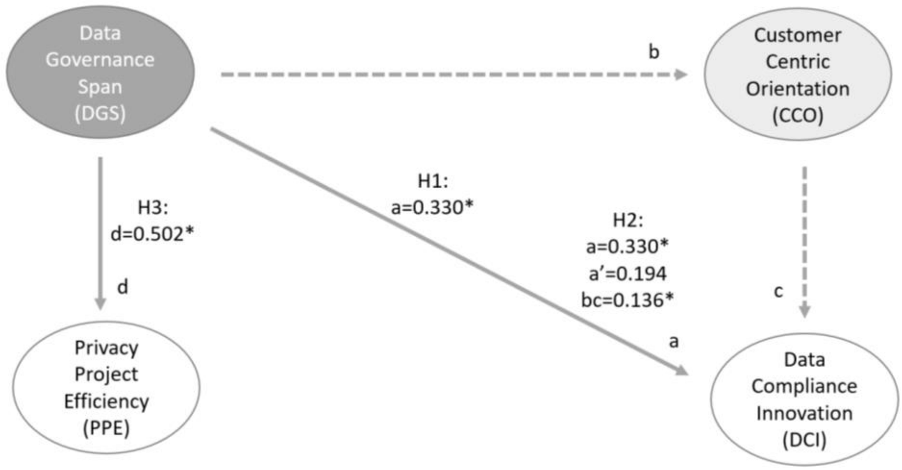
Source: authors

Data Governance Span (DGS) leads to the increase of both data compliance related variables at the same time, Data Compliance Innovation (DCI) and Privacy Project Efficiency (PPE).

However, its effect on the increase of Data Compliance Innovation (DCI) is weaker than the effect on the increase of Privacy Project Efficiency (PPE).

As it is a weaker direct mechanism of increase of Data Compliance Innovation (DCI), further exploration of the relationship between Data Governance Span (DGS) - Data Compliance Innovation (DCI) increased understanding on how it is possible to influence this relationship. As it leads to the increase of Data Compliance Innovation (DCI) itself, Customer-Centric Orientation (CCO) proved that it is actually an underlying mechanism of the relationship Data Governance Span (DGS) - Data Compliance Innovation (DCI).

Figure 2 | Primary hypotheses model results



Source: authors

Table 6 | **Hypotheses testing results**

	Original	Sample	Standard Deviation	T Statistics	P
			H1		
DGS -> DCI /	0.378	0.384	0.091	4.143	0
			H2		
DGS -> CCO	0.473	0.487	0.064	7.418	0
CCO -> DCI /	0.286	0.286	0.117	2.451	0.015
DGS -> DCI	0.330	0.325	0.107	3.079	0.002
DGS -> DCI	0.194	0.183	0.135	1.443	0.150
DGS -> DSI	0.135	0.139	0.061	2.213	0.027
			H3		
DGS -> PPE	0.502	0.500	0.082	6.125	0

Source: authors

5.4 Model Quality and Fit

Researchers using PLS-SEM rely on measures indicating the model's predictive capabilities to judge the model's quality. Unlike covariance-based SEM methods such as in LISREL, AMOS, and Mplus, variance SEM methods such as PLS do not support model fit indices such as Chi-square, Adjusted Goodness of Fit (AGoF), Normed-Fit Index (NFI), and Comparative Fit Index (CFI) (Chin, 1998). (Hair et al., 2017) suggest that Path Coefficient assessment is the safest way to evaluate a model. Another criterion known as Predictive Relevance (Q^2) can be used to inform model quality. Predictive Relevance is an indicator that assesses the model fit of structural (Chin, 1998). The blindfolding technique was used in SmartPLS to obtain construct cross-validated redundancy values known as the Sum of Squares of Observations (SSO) and Sum of Squares of Prediction Errors (SSE). Applying the formula by (Hair et al., 2017), the Q^2 value resulted in a good model fit (predictive relevance) of 0.175>0 (Esposito Vinzi et al., 2010).

Predictive relevance Q^2 and q^2 (e.g., use blindfolding; $Q^2 > 0$ is indicative of predictive relevance; q^2: 0.02, 0.15, 0.35 for a weak, moderate, strong degree of predictive relevance of each effect). For all dependent variables, values are in the range of moderate to strong.

Table 7 | Model Quality with Predictive Relevance Q2 from SmartPLS

	SSO	SSE	Q² (=1-SSE/SSO)
CCO	294	294	
DGS	392	338.986	0.135
PPE	98	74.361	0.241
DCI	98	85.628	0.126

Source: authors

The standardized root means square residual (SRMR) allows assessing the average magnitude of the discrepancies between observed and expected correlations as an absolute measure of the (model) fit criterion. A value of less than 0.10 is considered a good fit. Henseler et al. (2016) explains SRMR as a goodness of fit measure for PLS-SEM.

Normed Fit Index or NFI computes the Chi² value of the proposed model and compares it against a meaningful benchmark (Bentler & Bonett, 1980). The closer the NFI to 1, the better the fit. NFI values above 0.9 usually represent a more acceptable fit. Lohmoller (1989) provides detailed information on the NFI computation of PLS path models.

As defined by Henseler et al. (2016) d_LS (the squared Euclidean distance) and d_G (the geodesic distance) represent two different ways to compute the bootstrap-based discrepancy between the empirical covariance matrix and the covariance matrix. The upper bound of the confidence interval should be larger than the original value of the exact d_ULS and d_G fit criteria to indicate that the model has a "good fit".

In covariance-based SEM, the model quality measure is also a Bollen-Stine bootstrap (Bollen & Lennox, 1991). If more than 5 percent (or a different percentage if an α-level different from 0.05 is chosen) of the bootstrap samples yield discrepancy values above the ones of the actual model, it is not that unlikely that the sample data stems from a population that functions according to the hypothesized model. The model thus cannot be rejected.

Table 8 | Model fit results from SmartPLS

-	Saturated Model	Estimated Model
SRMR	0.089	0.101
d_ULS	0.360	0.456
d_G	0.148	0.170
Chi-Square	93.681	103.900
NFI	0.724	0.694

Source: authors

6 Conclusion, limitations and further research

6.1 Conclusion

This research contributes to a better understanding of intra-organizational dynamics within very complex and interacting economical and regulatory elements in the role of data in the digital economy. Economic, political and social activities are moving online, changing the interaction between individuals, businesses, and government, giving a wide scope for innovation. This extreme interoperability of the modern era creates a huge potential. Technology progress brings increasing opportunities for successive interactions in order to achieve profitable customer relationships. Organizations start storing and monetizing these data.

However, there are requirements for control that come with all these welfare effects. Regulators started to demand from firms conducting projects to ensure compliance. The study argues if such compliance spending then can also generate additional value. Compliance costs become more significant, and data related regulations are more frequent and will further increase.

However, the economics of data privacy, data compliance or data utility are still not fully understood (Duch-Brown et al., 2017); neither is there a sufficient amount of proven strategies that enterprises could rely on. Obviously, collecting, mining, utilizing or trading data can increase welfare and reduce economic inefficiencies, while at the same time, it can be a source of losses. It is unlikely that policymakers can answer questions on the optimal strategy to deal with the associated trade-offs, and enterprises need to search for these answers themselves.

While fulfilling compliance requirements, it would be beneficial to find mechanisms that bring positive influences in two self-contradicting directions, in exploration and exploitation, rather than in either one of them (Santa et al., 2011). Exploitation is the origin of efficiency, and hence, productivity, and requires a complete focus on improving given work. Exploration, as the origin of innovation, requires the opposite – to give away and re-focus to other realities and find new ideas.

Competitive advantage can be achieved by utilizing the GDPR opportunity to engage with customers in a new way and to innovate alongside that way, and to gain greater insight into their customers' needs (Sawhney et al., 2005). With a given mechanism, innovative firms would thus add more value to the data returned and displayed within data compliance requirements, enriching these data on the fly and with innovation in the dialogue with consumers. Data-driven innovations are becoming an increasingly vital feature of our societies, leading to growing data services channels with individual consumers or other economic subjects (Kumar et al., 2010).

Similarly, the compliance effort, if done right, should lead to better efficiency. Competitive advantage can be achieved by the fast and efficient establishment of organizational-wide roles accountability for privacy protection, as one of the key project activities in GDPR (Charlesworth & Pearson, 2013). There is an expectancy of new regulations with similar project requirements, where constant speed in their fulfilment - can be a differentiator. In modern times, the ability to quickly adjust to frequent changes in response to market or compliance requests raises the importance of operational efficiency (Slack et al., 2013).

On the other hand, the path towards such beneficial 'use GDPR compliance to explore and exploit' strategy requires a coordinated organization involving different entities, including legal, human resources, marketing, security and IT and their integration. Information aspects nowadays clearly override the domain of information technology (Kooper et al., 2011) – demanding data governance-driven constant improvement in communication between departments (horizontal) and between management levels (vertical) (Orr, 1998). Such data governance arrangements can compensate for the rigidity of the organizational structure and help organizations to achieve two seemingly conflicting objectives– efficiency and innovation (Korhonen et al., 2013).

In such a new data compliance-driven environment, this research project explores ways for achieving adequate vertical integration strategies, combined as well with horizontal strategies of integration - which has been a challenge for managers for a long time (Galbraith & Lawler, 1993) and (Mintzberg, 1979; Porter, 1998). This research offers a 'span of data governance' as a management tool to increase both innovations in data compliance project and efficiency in privacy accountability - in the same project, at the same time. This is suggested in the GDPR case. The privacy project efficiency is more strongly impacted by that span. Further exploration of the weaker relationship (towards innovation) increased our understanding of how it is possible to influence it. Customer-centric orientation proved to be an underlying mechanism of that relationship, and it should be an active parallel strategy in addition to the data governance span strategy.

Based on an extensive review of the previous literature, data governance is either placed narrowly and tactically (as a particular technology solution) or very broadly - referring to the value of its strategic utilization, often seen as abstract, without practical implications. This work develops a framework that attempts to bridge these two through the concept of data governance span, thereby introducing a new interpretation of data governance, and arguing that exactly filling this gap and making this bridge - is necessary to achieve effective execution of data governance and 'fruitful' data strategy as well.

All hypotheses of this study are organizational practice driven. Many enterprise-wide information management concepts, considered as an immense investment and as a failure at the same time -eventually lacked the proper support in organizational practices (Silvola et al., 2011). Investigating data governance and intra-organizational dynamics within this complex environment helps us find a balance between information sharing and information hiding that is in the best interest of data holders (enterprises), data subjects (individuals) - but also of society as a whole (Acquisti et al., 2013).

6.2 Further research

The natural next step would be theory confirmation of the whole exploration-driven research model by using some of the variance-based SEM methods and a larger amount of records. Further research might complement this work through a more thorough process of building constructs, its rationalization, and operationalization with a higher number of indicators. It is a good opportunity for other researchers to look into results that they can gain from an unused area of starting abstract concepts.

The research showed indices of some potential and interesting differences between different regions and industries, which may be a topic for another, more narrowly defined study.

Further understanding of intra-organizational dynamics and mechanisms to gain over the potential costs will provide necessary insights for the competition, authorities, and regulators in order to react to the new challenges of the digital economy. There are no strongly-argumented policy solutions yet, and more research is required to bring economics up to speed with these questions (Duch-Brown et al., 2017). Expected changes in data regulations will bring opportunities to adopt findings from this research or to validate them in a new changed setup.

6.3 Limitations

The number of items in a measure:

While this work was focused on efficiently intersecting multiple research domains, a long list of items demands much more time in both the development and administration of a measure (Carmines & Zeller, 1979). Responses are asked from senior members associated with data management, data governance or compliance. They are considered as ‘high profiles’ and in senior management positions, not taking time to fill in online surveys. This triggered the decision on minimization of survey questions. Additionally, keeping a measure short is an effective means of minimizing respondent fatigue biases (Schriesheim & Eisenbach, 1995).

Constructs used in this study are concrete, where objects and their characteristics are perceived similarly by all raters, aiming for a unanimous agreement by raters to what it is (Diamantopoulos, 2005). It was simply measured whether or not there was more innovation in the project compared to the competition or whether or not the project was done faster than the competition. When a construct is judged to be concrete, the use of single-item measures is considered reasonable (Sackett & Larson, 1990). Likewise, constructs in the project are accurately and in detail described and made clear to respondents in the instrument, and there is an operational definition prior to a question in the survey, which is a requirement for successful usage of single-item measure (Sackett & Larson, 1990).

The aim with new yet nonmeasurable constructs in the model was to allow a respondent to consider the certain aspects of the construct being measured (Nagy, 2002), putting slight pressure on the respondent to provide a general rating of its level perceived. Multi-item measures tend to provide biased results in such cases.

When the existing scales were carefully scrutinized across a range of research domains, it was found their items are often semantically similar and therefore redundant. This further motivated the researcher to present a reduction in the number of items (Smith & McCarthy, 1995) and show the same error variance associated with redundant items (Drolet & Morrison, 2001).

There is a multi-item construct of data governance span at the heart of a study (four items), with the intention to generate specific insights into the nature of that construct. On the other hand, when it comes to innovation and project efficiency in GDPR, the aim was to obtain only a general view of the construct, and the research objective is to get an overall judgment or impression of it. The single-item measure is often adequate for this purpose (Poon et al., 2002).

Finally, variance-based SEM (dedicated to theory exploration) does support constructs with single items (Gefen et al., 2000). However, scales with too few items may lack content and construct validity, internal consistency and test-retest reliability (Kenny, 1975) and - this remains a limitation of the study.

Sample size:

Obtaining large samples can be very costly. Responses are asked from 'high profiles' and in senior management positions, where many do not take the time to fill in online surveys. This triggered the decision on a smaller sample size in order to ensure the collection of a sufficient number of answers from the right people.

Variance-based SEM is focused on theory exploration rather than confirmation and supports a small sample size, e.g. < 100. It is advantageous during data analysis where no distributional assumptions are required (Hock-Hai et al., 2003).

However, the sample size determines the significance of correlations in research models and a greater data collection sample size provides a higher statistical power of the model, giving higher value to the coefficient of relationships. This remains a limitation of the study.

Construct conceptualization:

Constructs used in this exploration work were conceptualized and adjusted from some of the existing ones.

Variance-based SEM does not necessarily entail strong prior theories and established operationalizations.

However, the extensive process of construct conceptualization in the form of qualitative research and with multiple phases of construct development test results with more indicators is suggested for other authors and remains a limitation of the study.

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