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Data compliance with cross-functional governance team leadership and customer-centric operating model

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Declaration of Authenticity

I hereby declare that the dissertation thesis presented herein is my own work, or fully and specifically acknowledged wherever adapted from other sources. This work has not been published or submitted elsewhere for the requirement of a degree programme.

In Prague, 30th of June 2019. Milomir Vojvodic

In memory of Jovanka Vojvodic (1957-2017)

May more doctorates and more people in this world find examples that inspire and oblige.

For your kindness and that selfless dedication that made us feel so loved and special,
for your genuine integrity, strength, and responsibility that reflected your children,
for the lessons from your school of beauty in strive and in creations,
for an example of an honorable life as it should be,

I thank You.

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Abstract

This research investigates the economics of data, levels, and aspects of utilized benefits associated with their economic potential in the data economy, levels and aspects of their efficient control for compliance purposes - considering the new regulatory framework of European Union and General Data Protection Regulation (EU GDPR). Compliance costs are significant and data related regulations are more frequent. The study argues if compliance spending then can also generate additional value, as just a minimal regulation requirements fulfillment is not by any means achieving a competitive advantage. The value is narrowed to the fields of innovation and operational efficiency in this exploration driven quantitative research. Rather than in technological, the aim of the project is to look in governance and leadership related organizational practices for empirical proof, where multiple predictor, mediator, and moderating variables were measured in order to offer a range of potential managerial interventions. To test the hypotheses, a quantitative method with Structural Equation Modelling and Partial Least Squares (PLS) in SmartPLS tool is used. The empirical data is collected from 98 data management professionals involved in recent GDRP projects associated with party data in larger organizations across Europe. The study proves 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 Data Governance Span (DGS) - Data Compliance Innovation (DCI). Governance Teal Leadership (GTL) leads to the increase of both Data Governance Span subconstructs at the same time: Cross-Functional Integration (CFI) and Line-of-Business Stakeholders Participation (LOBSP), and this effect is stronger on the former subconstruct.

Key words: governance, data compliance, organizational design, customer-centricity, leadership

1. 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 afterward. Minimal regulation requirements fulfillment 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, which otherwise could have never gotten funded - if not included under the umbrella of an unavoidable compliance project. Meanwhile, business structures are evolving over time at a faster rate, and enterprises grow and interconnect increasingly. Moreover, answering this return-on-data-compliance question is further challenged with continuing issues in the slow movement of information management from low-level operations towards managerial functions and line-of-business users across the enterprise.

This research argues if compliance spending then can also generate additional value. The value is narrowed to the fields of innovation and operational efficiency. Rather than in technological, the aim and objective of the study are to look in organizational practices for empirical proof, where multiple predictor, mediator, and moderating variables were measured in order to offer a range of potential managerial interventions.

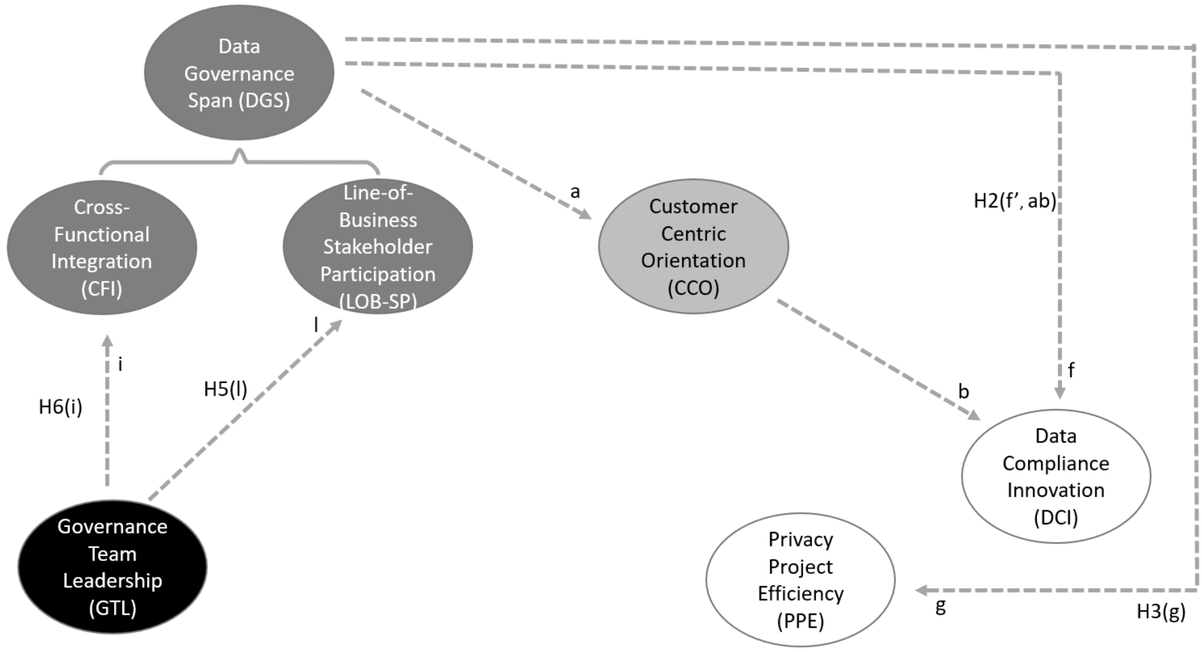
The study examines the impact of data governance cross-functional and business stakeholders span on innovation in compliance management when it comes to interaction with the customer. The impact will be considered through a mediating role of customer-centric organizational orientation. In parallel, the impact of the same governance span on compliance management operational efficiency is explored, in the implementation of privacy accountability processes. Finally, the work adds an analysis of the effect that resistance-aware, leadership-driven governance team change agents bring.

Design/methodology/approach:

Several variables in this exploration driven quantitative research are investigated as potential managerial tools. The focus of the research is developmental, exploratory, causal modeling and theory building, rather than theory confirmation.

To test the hypotheses, a quantitative method with Structural Equation Modelling and Partial Least Squares (PLS) in SmartPLS tool is used. The empirical data is collected from 98 data management professionals involved in recent General Data Protection Regulation projects associated with party data in larger organizations across Europe.

Figure 1: Primary hypotheses research model



Source: Author

Data Compliance Innovation and Privacy Project Efficiency

This 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) (Figure 1).

The European Union General Data Protection Regulation, 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.

Economics of consumers' data and customers' data, the level of utilizing benefits associated with the potential that these data carry and the level of its effective control within the regulatory framework of EU GDPR is to be used for measuring the success of applied organizational practices. The reason for information issues lies in the fact that the greatest challenge to success is not so much technological as it is organizational. Both, compliance with regulations while advancing in commercial customer-centric data usage - cannot be achieved without modernizing existing lines of business systems.

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. Simple GDPR requirements fulfillment does not in any way gain competitive advantage, while 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 on the market. The proposed changes are a chance for businesses to gain greater insight into their customers' needs (Sawhney, Verona, & Prandelli, 2005).

Likewise, the advantage could be gained with the efficiency and performance of the necessary compliance project, if it provided maximum or necessary results with fewer investments than other similar companies. Establishing organizational-wide roles accountability for privacy protection and appropriate use of personally identifiable information (PII) is one of the key project activities in GDPR (Charlesworth & Pearson, 2013). With adding more value to the data returned and displayed within data compliance requirements, enriching the data on the fly and with innovation in the dialogue between consumers and organization - it is possible to adopt a customer-centric engagement model alongside compliance-driven activities (Kumar et al., 2010). 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.

Data Governance Span

The organizational practice driven information governance dimension of this research is the Data Governance Span (DGS) construct (Figure 1).

At the present time, companies transform and look for their ideal role in the data economy (Opher, 2016). Management of the data about individuals and customers in the enterprises is not just internal business anymore as regulations such as GDPR do take over part of the control of it. Subsequently, this work investigates transformational ways that EU companies can then use this regulation for competitive advantage, focusing on organizational practice.

As per Korhonen et al. (2013) relating organizational approaches or practices to the field of data, including data compliance, leads to the governance concept. Internationally agreed upon regulations such as Sarbanes-Oxley in the US, and Basel and GDPR in the EU, enforce strict corporate governance policies that have an elementary impact on the roles and responsibilities among peers in information management. Governance becomes a strong need for data management in modern, regulation-driven conditions. Ad hoc, siloed and mutually disconnected automation projects brought complex information landscapes characterized by redundancy and inconsistency. Firms are aiming to break down the silos of information and unlock trusted information to flow freely to where it is required. At the same time, appropriate safeguards and measures need to be put in place to protect sensitive information and fulfill compliance requirements (Korhonen et al., 2013).

Addressing GDPR compliance requires a coordinated strategy involving different organizational departments. Successful compliance cannot be achieved without a seamless and secure information strategy across the various entities. In turn, this would require well-coordinated wide-spanning organizational involvement in addition to the technologies.

Proper utilization of organizational practices on the top of holistic IT programs still suffers from IT and business misalignment. Governance is not an exception. Challenges still exist in this area with relatively little success of attempts to increase the span of data governance across more functions and across more business stakeholders. Information and data become an organic part of processes and activities. Very collaborative, cross-functional and IT-business aligned governance processes need to be established as changing core data often means changing business processes and is becoming exceedingly frequent nowadays (Delbaere & Ferreira, 2007). As stated by

Davenport and Short (1990), individual tasks and jobs change so fast that there is no point redesigning them.

Customer-Centric Orientation

This customer related dimension is operationalized as Customer-Centric Orientation (CCO) in this research (Figure 1), and it is expected to be influential in the way of how 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). 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). This is consistent with the direction given by Kim and Maubourgne (1997) and Prahalad (2016) where those that aim to do more than that – need to look for deep and unusual insights that anticipate trends and changes, and need to identify new products and services to offer - before the competition and even existing customers think of them themselves.

For example, 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. However, as an approach, it requires cross-functional synchronicity and integration as well as changes in organizational structure and processes (Shah, Rust, Parasuraman, Staelin, & Day, 2006). Fader (2012) and Marsh (2010) caution that customer centricity, along with compliance with regulations and data utility - cannot be achieved at all without modernizing the existing line of business and implementing tighter cross-functional integration mechanisms. The former is seen as a case of vertical integration and the latter as horizontal integration.

The success of the company is directly influenced by both internal integrations, vertical and horizontal, as they are prerequisites for successful external integration, with customers for example. The power of organizations and teams is not in the mythical figures of direction and influence, but in the knowledge that is shared vertically and horizontally by all its members (La León de Barra, Galdames, Crawford, Soto, & Crawford, 2015). As customer data has become embedded in nearly every department and business unit, a proper governance program requires organizational change and much more rigorous cross-functional alignment (Payne & Frow, 2005).

Line-of-Business Stakeholders Participation and Cross-Functional Integration

Following this, Data Governance Span (DGS) is then rationalized as a higher order construct consisting of two lower order constructs (Figure 1): Line-of-Business Stakeholders Participation (LOBSP) within Data Governance Span (vertical integration) and Cross-Functional Integration (CFI) within Data Governance Span (horizontal integration).

The best practices from strategic management, business process management, risk management, and IT governance are combined in the information governance concept (Niemi & Laine, 2016). It moves the data management profession from low-level operations towards managerial functions, increasing the participation of business stakeholders. Friedman (2007b) suggests that cross-functional adoption of data governance increases the ability to manage data issues enterprise-wide and to have smoother resolution and cross-departmental monitoring. Formation of a common data model for customer data can be followed with its extension into enterprise data as a service - driving the success of customer-facing functions operations.

This can also bring a competitive advantage. In addition, effective and cross-functional data governance has been suggested as being critical in obtaining utility from data use. Davenport and Short (1990) argue that vertically and horizontally spanning team-oriented, coordinative, and communication-based work capability - should be the carrier of an activity task outcome, instead of a single role. Such speed in constant changes on role assignments side - diminishes importance in maximizing the performance of an individual role or performance of the standalone business function. The aim is rather to maximize interdependent activities that horizontally and vertically span across the company.

This construct split might exactly point out and prove the cause of the explored organizational practice mechanisms that bring positive influences in both directions, innovation and efficiency, rather than in just one of them. By having both, the vertical control structure and horizontal collaboration structure in place, the organization can flexibly adjust its behavior to varying business priorities and find an appropriate balance between efficiency and effectiveness, or between exploitation and exploration (Santa, Bretherton, Ferrer, Soosay, & Hyland, 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 finding new ideas. With a given mechanism, EU companies could use GDPR regulation as a competitive advantage, as a means for innovation and further efficiency, clearly resulting in data regulation associated benefits exceeding their costs to comply.

Such governance arrangements can compensate for the rigidity of the organizational structure and help organizations to achieve two seemingly conflicting objectives (Korhonen et al., 2013) that arguably could not be combined successfully at the same time – efficiency and innovation. Tidd and Bessant (2013) looked for a formula for firms to combine both arguably contradicting abilities - to be operationally effective in exploitation (GDPR efficiency) and strategically flexible in exploration (GDPR innovation).

Governance Team Leadership

Besides the governance challenges originated from IT and business misalignment, and lack of participation from business functions and business stakeholders that are rationalized in the Data Governance Span construct, there is one more domain with expected influence on the research problem. Despite the growing importance of such holistic cross-organization initiatives, a considerable number of organizations continue to struggle with their governance programs as they resist, seeing such a program as a large-scale undertaking, where its effective implementation can be 'too big of a change' and transformational (Mittal & Dhar, 2015). Drucker (2009) supports this with the claim that resistance against organizational change is a primary reason for the inefficiency of operations. As many researchers have demonstrated, leaders and influencers play a major role in IT implementation success or failure, and there is a need for specifications of program leader behaviors and suggestions to management by integrating dynamics of resistance with leadership theories.

Data stewards hold a crucial role in the execution of the data governance program and can be seen as major change agents and program leaders. Plotkin (2013) suggests that they are key representatives in a specific business area responsible for the quality, use, and meaning of that data in the organization. They are responsible for communicating changes to data policy, regulations, and rules, acting as the point of contact for data-related issues, and attempting to arbitrate and mediate conversations between business and IT and work across enterprise departments.

Governance Team Leadership (GTL) is the integrative construct that refers to the team of data stewards and their leadership in dealing with change resistance (Figure 1).

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 are two additional *supporting research questions*: Can the relationship between this span and data compliance innovation be explained with customer-centric orientation? Do proactive leadership-driven data stewards impact this span in both directions, horizontally (cross-functional span) and vertically (span in business stakeholder participation)?

Findings can be divided into three sections:

1-The role of governance span and customer-centricity in achieving two seemingly conflicting objectives in compliance efforts, innovation and efficiency at the same time:

Data Governance Span (DGS) leads to 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).

As it is a weaker direct mechanism of increase of Data Compliance Innovation (DCI), further exploration of the relationship between Data Governance Span (DGS) and Data Compliance Innovation (DCI) increased our understanding of 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).

2-Introduction of leadership and its influence on governance span:

As it is such a strong direct mechanism of the increase of Privacy Project Efficiency (PPE), further exploration of Data Governance Span (DGS) showed how it is possible to influence change in this construct - Governance Teal Leadership (GTL) leads to the increase of both Data Governance Span subconstructs at the same time: Cross-Functional Integration (CFI) and Line-of-Business Stakeholders Participation (LOBSP).

As it is a direct mechanism of increase of Data Governance Span (DGS) - further exploration of Governance Teal Leadership (GTL) showed the difference in how it is possible to influence change in this construct. While Governance Teal Leadership (GTL) leads to the increase of both Data Governance Span subconstructs at the same time, Cross-Functional Integration (CFI) and Line-of-Business Stakeholders Participation (LOBSP), it has a much higher impact on the increase of the former than on the latter one.

3-Other results of the exploration of the relation between leadership, efficiency, and governance:

At the same time, Governance Teal Leadership (GTL) leads to the increase of Privacy Project Efficiency (PPE) through the 'stronger' Data Governance Span subconstruct (Cross-Functional Integration (CFI)), but not through the 'weaker' one - Line-of-Business Stakeholders Participation (LOBSP).

Further exploration of this 'stronger' data governance span variable (Cross-Functional Integration (CFI)) and how it leads to an increase of Privacy Project Efficiency (PPE) showed there is the use of the 'weaker' data governance subconstruct as it increases the strength of the relationship. The impact of Cross-Functional Integration (CFI)) on Privacy Project Efficiency (PPE) can be strengthened through Line-of-Business Stakeholders Participation (LOBSP).

Research/practical implications:

Achieving adequate vertical strategies combined as well with horizontal strategies of integration is a challenge for managers (Galbraith & Lawler, 1993; M. Porter, 1998) and there is value in the research that develops useful ways to categorize them both (Mintzberg, 1979).

The explored organizational practice mechanisms 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 governance provides a means to obtain utility from controlled data use, which is crucial in the current data economy. Furthermore, it is possible to tune multi-domain organizational practices in the back-end (leadership, change management, organizational design, go-to-market) 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 proves this in the GDPR regulation case. Increase in innovation is achieved if customer-centric orientation is used as an active strategy alongside governance span. Moreover, to increase the span - governance team leadership should be called for, through building team identity and knowledge transfer in work schedules.

The span of data governance is further substantiated for managers. Horizontal span or cross-functional integration is the primary way how managers can use governance team leadership to positively impact project efficiency. To adopt this horizontal span within a data governance framework, it is necessary to measure a share of information and ideas between functions; as well as to measure a cross-functional communication to resolve data issues. Eventually, managers can use vertical span or line-of-business stakeholders' participation to increase the strength of cross-functional impact. Vertical span undertakes involving business stakeholders in formal engagement which assumes their responsibility and in the formulation of objectives, evaluation of results and use of outputs.

The scientific body of knowledge does not record empirical evidence of organizational practice needed for successful implementation of a compliance-driven information governance program, certainly not under GDPR regulation. This work attempts to contribute to filling the gap. In order to support the 'practical implications driven' theory building, it adds multiple domains in exploration, empirically evidencing for the first time impacts between various new variables. Additionally, this research is supposed to add to prior literature with the empirical evidence and categorization of interaction in the focal research domains (governance, leadership, marketing, innovation, and efficiency). In the body of knowledge, governance is found either as 'too technical', restricted to a particular technology solution, or very broad and 'too strategic', often seen as abstract, without practical implications. This work develops a framework to bridge these two through the concept of governance span, thereby introducing a new interpretation of data governance, and arguing that - precisely filling this gap is necessary to achieve effective execution of governance programs with a tradition of failures. Moreover, the work argues that the framework can be extended into a mechanism for success in wider data strategy - if properly combined with market orientation and leadership research.

Research Gap:

Research on data governance is still in the early stages (Alhassan, Sammon, & Daly, 2016). 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, Maes, & Lindgreen, 2011). Its 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, leadership, innovation, and efficiency. There are no empirical studies available on any of the relations in the above-stated issues. Even if qualitative research covering the design and implementation of information governance in an organizational context exists, empirical evidence in the form of quantitative research is missing (Niemi & Laine, 2016). The results from Alhassan et al. (2018) validate identified research gaps and concerns that the scientific publications on data governance are almost exclusively focused on defining activities; while implementing and monitoring challenges are seen mainly or only in practice-oriented publications. The studies rarely explain in detail the activities necessary to successfully conduct a governance program.

In the same way, there is a lack of view on 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. As well, cross-functional project teams utilization has generally received little attention from researchers, and especially in its association with information systems (Koulikoff-Souviron & Harrison, 2006).

Business structures are evolving over time, and enterprises grow and are increasingly interconnected. Practice demands studies with the key words 'consistent' and 'holistic' and demands for ways that integrate both, the cross-functional views and business-stakeholder-recruitment views (Berson & Dubov, 2011). Achieving adequate vertical strategies, combined with horizontal strategies is a challenge for managers (Galbraith & Lawler, 1993). Porter (1998) had the same conclusion - stating many years ago that the pending task for researchers is to develop useful ways to categorize these strategies. Furthermore, an alignment of IT and business strategies can generate a sustainable competitive advantage and increases profitability (Kearns & Lederer, 2003).

No previous study has investigated empirically either innovation or efficiency achieved in compliance projects. Generally, research on improving cycle time in capital projects is limited (Ancona, Goodman, Lawrence, & Tushman, 2001). Successful projects are often based on the actual management of people in the project, as argued by Belassi and Turkel (1996), and there are literature absences in the recommendation of proven team practices (Kloppenborg & Opfer, 2002).

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

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 technological 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.

At the same time, few studies have proposed theoretical explanations and there are still gaps in the understanding of underlying mechanisms from the fields of organizational design, leadership, and organizational psychology. Where some of the explanations and different concepts do exist in the research of change management and leadership - there are still rare insights in how to employ the theories on the concrete state of the art issues such as a compliance project (Laumer, 2011). Based on an extensive review of the previous literature, 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.

Method:

The focus of the research is exploration, causal modeling and theory building, rather than theory confirmation. The major idea of the research is practical, with a focus on applied scientific nature and predictive study, exploratory rather than explanatory, self-correcting with built-in checks along the way. The aim of the project is empirical (perceptions, beliefs, and attitudes carefully checked against objective reality), with the objectives of solving real problems rather than just gaining knowledge; predicting effects and finding causes; developing interventions rather than theories. While the first-generation techniques, such as correlations, regressions, or difference of means tests (for instance ANOVA or t-tests), offer limited modeling capabilities - the second-generation techniques (covariance-based Structural Equation Modelling (SEM) and Partial Least Square (PLS), offer extensive, scalable, and flexible causal-modeling capabilities. Therefore, the latter statistical method was selected. In particular, SEM and PLS allow for complex models that include latent (unobserved) variables, formative variables, chains of effects (mediation), moderation, and multiple group comparisons of these more complex relationships (Lowry & Gaskin, 2014).

Structure:

This study is composed as follows: After this introduction, there is a section of theoretical background that starts with a review of the governance, including a highlight on business stakeholders' participation, cross-functional governance, and data stewardship. The chapters that follow are focusing on customer centricity, leadership, change and resistance management, innovation and efficiency as a part of compliance management. The theoretical background ends with a chapter on data economy, economics, regulations and its connection to data governance. The next section includes a chapter on the research model and conceptual framework with the theoretical background behind the hypotheses followed by a chapter on the research method, including data collection, operationalization, and instrument explanation and data pre-analysis. The discussion section gives the details of the results obtained. This work ends with a conclusion, a summary of limitations and suggestions for future research.

2. THEORETICAL AND PRACTICAL CONTRIBUTION

Practical contribution:

The research project is meant to integrate theories from microeconomics, organizational design, as well as marketing and organizational psychology, with several practical inter-related state-of-the-art business and research problem domains. This integrative perspective has the aim to provide a useful tool for managers needing to assess the likelihood of effective strategies and will help them understand the effects of their acceptance - in order to proactively design interventions.

The need for governance to seriously assess aspects of business services such as regulatory compliance and quality 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 the most important change in data privacy regulation in the world in twenty years. It 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, 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.

Both costs and benefits variables have their own complexity. Besides the cost of regulations in fines, firms can be severely punished by the market itself - if perceived as invasive of consumers' privacy for instance. There are a number of reasons for the severe drop in willingness to engage in transactions with non-reputable firms (Goldfarb & Tucker, 2011). Calo (2011) lists intensive subject privacy harmful effects even in psychological discomfort or embarrassment. This may drive the number of enterprises to overspend on technologies and services in data gathering, mining, and processing in order to avoid risks of privacy debacles.

Different functional areas are managing and continually enriching and optimizing a common data set of data and customers' data independently. 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). Data-driven innovations are becoming an increasingly vital feature of our societies, leading to growing data services dependence by individual consumers or economic subjects. Ideally then, the compliance effort, if done right, should lead to better efficiency and innovative new business initiatives - which otherwise would never be funded.

Obviously, collecting, mining, utilizing or trading data can increase social welfare and reduce economic inefficiencies, and 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 such answers themselves. This research offers and proves new options for managerial mechanisms that bring positive influences in both directions, costs, and benefits, through efficiency and innovation.

Governance has been suggested as critical in obtaining utility from data use. It provides value to traditional information management by expanding its span, involvement, and alignment with business stakeholders and cross-functional handling of data issues. Communication between departments (horizontal), and between management levels (vertical) is crucial in primary processes and workflows to improve the adaptability of data governance measures (Orr, 1998). Achieving adequate vertical strategies, combined as well with horizontal strategies is a challenge for managers (Galbraith & Lawler, 1993; M. Porter, 1998) and this work contributes with categorization - followed by a clear action plan.

There is a need to avoid governance being positioned as a huge challenge and transformational as it has complex organizational, change-resistance-related, psychological, and then consequently program-outcome-related implications. This study elaborates on a leadership driven approach that supports a light, non-threatening, non-interfering, non-culture-changing, non-invasive way - reducing the challenges people in a company may have in accepting the 'new' governance.

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. The research proves this in the GDPR regulation case. The former is achieved in customer-centric orientation as an active parallel strategy in addition to the governance span strategy. The customer-centric operating model even has an additional positive impact on the governance span itself, as it proposes organizational design changes and integration of customer-facing functions and metrics - contributing to the overall cross-functional governance integration.

If it is necessary to increase the span – governance team leadership should be called for (leadership in the building of team identity, communication and knowledge transfer in the work schedule). When the span of data governance is further substantiated for managers - it is visible that the horizontal span (cross-functional integration) is the primary way of how governance team leadership positively impacts project efficiency. To adopt it within a data governance framework there must be enabled an intensive share of information and ideas between functions and cross-functional communication to resolve data issues. Vertical span or line-of-business stakeholders' participation can increase the strength of this impact. It consists of involving business stakeholders in formal engagement which assumes their responsibility and in the formulation of objectives, evaluation of results and use of outputs.

Existing governance tools lack efficiency in several areas including business alignment, measurement, data definitions, policies, and stewardship. The evolution of governance processes with more dynamic policy changes - will only exacerbate this efficiency problem. In parallel, the customer has a tendency to comment on 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, 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, Jaaskelainen, Kropsu-Vehkapera, & Haapasalo, 2011). That very missing part is considered a major reason for their failure. This work goes further and offers multiple-domain organizational practices in the back-end (leadership, change management, 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.

The research project integrates compliance with governance in empirical testing. Ensuring compliance with legal and regulatory provisions is the business goal most frequently mentioned in the literature on data governance (Delbaere & Ferreira, 2007).

This project provides an opportunity to advance the overall understanding of the rising role that data economy, compliance and governance have in the organizational context. Progress in such understanding contributes to the debate on overall society welfare-maximizing aims. Personal and customer data protection may increase or decrease economic efficiency in a marketplace (Acquisti, 2013), and their emergence as an asset then demands more factual, empirical analysis (OECD Organisation for Economic Co-operation and Development, 2014). This research contributes to a better understanding of intra-organizational dynamics and internal trade-offs that play an important role in the open market. Given all these arguments about the importance of data, researchers need to help us more in understanding how individuals and organizations make decisions about usage data, and what are the consequences of such decisions.

Theoretical contribution:

Integration of theories from microeconomics, organizational design, marketing, and organizational psychology - while practically and empirically inter-relating several state-of-the-art business and research problem domains - is a major theoretical contribution of this work. The field has weaknesses in 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 governance, customer-centricity, leadership, efficiency, innovation within the research of the others. The integration process in which the overlap between two research domains is identified - follows the conceptual framework for incorporating two constructs into one line of research. The framework clarifies the relationship between these two. Then, some of the critical relationships are empirically tested in the conceptual model. Eventually, all of them are examined in a new setting of the data compliance regulation of modern times. This broadens the application of each of the respective constructs.

Prior empirical research on data governance and the relationship between data governance and business strategy - has frequently been criticized for its methodological shortcomings. 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.

Achieving adequate vertical strategists, combined as well with horizontal strategists is a challenge for managers (Galbraith & Lawler, 1993; M. Porter, 1998) and this work contributes in its categorization (Mintzberg, 1979). The study aims to contribute to the existing literature by helping to achieve a better understanding of the diversification of activities in the area of the leadership of governance teams, cross-functional integration and line-of-business stakeholders' participation - and to offer empirical evidence that could lead to recognizing best practices.

The research followed the practice of establishing the empirical linkage between two constructs and to establish the third construct as a potential mediator in between. Such an investigation is of interest to the field of organizational behavior 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 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 theories from leadership and marketing, transformational leadership theories from Bass (1985) and Burns (2003) and market orientation theory from Narver and Slater (1990) and Jaworski and Kohli (1993).

In addition, the study deepens some of the existing theories by offering a new perspective on the application of their portions into the real-world and state-of-the-art problems in the field of the data economy, information governance and compliance. Particularly, this exists in five sections: in line-of-business stakeholders' participation theoretical review: involvement and appreciations from the theory of Swanson (1974), Juran and Feo (2010) with total quality management theory, the stewardship theory of management (Davis, Schoorman, & Donaldson, 1997); in cross-functional integration theoretical review: ontology engineering theories and methods to reach a consensus (Holsapple & Joshi, 2002), organizational integration from Leavitt (1964); in customer-centric orientation theoretical review: cooperation and coordination (Lawrence & Lorsch, 1967), the way Hult (2011) delineated a theory of the boundary-spanning marketing from Day (1994), Thorelli (1986) and theory of network of organizations; in governance team leadership theoretical review: Brown and Magili (1994) with the principles of contingency theory transferred to the organisation of the IS, Bono (2003) and transformational leadership theory with the self-concept based theory, strategic choosing theory from Child (1997), interaction theory from Markus (1983); and in data compliance innovation theoretical review: theory of information asymmetry (Akerlof, 1970), and strategic innovation from Krinksy and Jenkins (1997).

3. THEORETICAL BACKGROUND

This segment of the dissertation aims to demonstrate an understanding of concepts applicable to the topic of the research and relates to the broader areas of knowledge being considered, together with the reference to relevant scholarly literature. It is organized according to the list of major constructs used in this quantitative research: Data Governance Span (DGS), Governance Team Leadership (GTL), Customer-Centric Orientation (CCO), Data Compliance Innovation (DCI) and Privacy Project Efficiency (PPE). The last section covers state-of-the-art concerns in the field of data economy, regulations, and governance that contribute to the relevance of this research at the present time.

3.1. DATA GOVERNANCE SPAN

This part of the theoretical background conceptualizes the Data Governance Span (DGS) that is rationalized as a higher order construct consisting of two lower order constructs, Line-of-Business Stakeholders Participation (LOBSP) within Data Governance Span (vertical integration), and Cross-Functional Integration (CFI) within Data Governance Span (horizontal integration). Additionally, before and after the construct conceptualization material, the section covers information and data governance, data governance organizational nature and governance team of stewards afterward.

3.1.1. INFORMATION AND DATA GOVERNANCE

The following section gives an overview of governance definitions while highlighting the need for 'span' of governance as its important attribute.

Data governance has rapidly gained in popularity (Khatri & Brown, 2010). Furthermore, in the research of governance, the term data is in the past years frequently being replaced by the term 'information' (Tallon, Ramirez, & Short, 2013). However, both information and data governance form a relatively new research area as described by Niemi and Laine (2016). The origins of the information governance idea can be found in the 1990s in the work of Goodhue (1990), where it is related to the strategic planning of information resources and includes conceptualization of even information as a product. Initial attempts to create a framework for information governance came two decades later from Brackett (2010) and Wende (2007), and at the same time, stronger scientific definitions appeared (Weber, Otto, & Österle, 2009).

Information management challenges to become effective, proactive, and predictable have to be addressed by the concept of governance (Berson & Dubov, 2011). Potentially, this is one of the ways to explain the appearance and popularity of the concept. The signs of the data management profession progressing from low-level operations towards managerial functions can be seen through such overarching concepts like information governance. Information aspects have taken over the domain of information technology (Kooper et al., 2011) and it is a natural consequence to data management to start entering the space of hierarchal higher order constructs.

One of the key issues of information management, the ontological nature of data, is addressed successfully by governance (Iivari, Hirschheim, & Klein, 1998). Governance aims to clarify the understanding of the meaning of the various representations of data or information, as well as different approaches to interpreting such representations, on a continuum from universal to contextual.

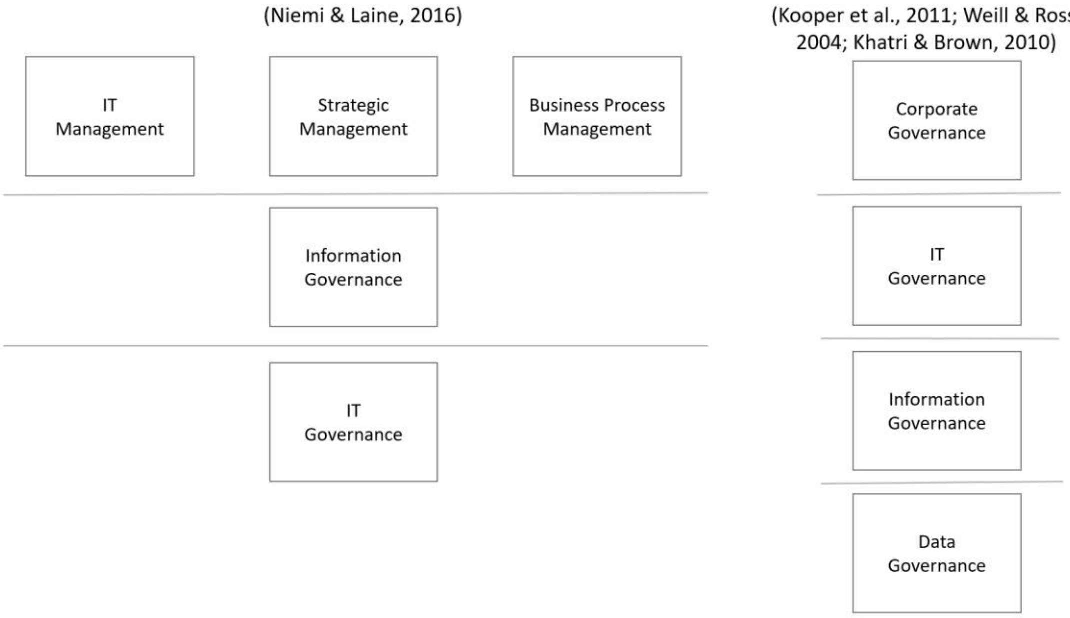
Business practice differentiates information from data naturally and designates information as data that has been processed in some way, although the terms data and information are often used as synonyms (R. Wang, 1998). For Korhonen et al. (2013), it is an organizational approach to both data and information management that formalizes a set of policies and procedures to encompass the full life cycle of data, with the accent on gaining consistency, and the consistent view from collection till archival or deletion 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, implemented according to agreed-upon models clearly designating who can take what actions with what information, and when, under what circumstances, and using what methods.

There is an additional concept that is intersecting both data and information governance. It is IT governance. As data governance is a newer discipline, many of its concepts are derived from IT governance. In the works of some authors, IT and data governance are interrelated but autonomous disciplines (Kooper et al., 2011; Weber et al., 2009). It is IT governance. For Niemi & Laine (2016), information governance is a strategically higher order concept than IT governance, as they argue that the best practices from strategic management, business process management, risk management, and IT governance are combined in the information governance concept (Figure 2).

There are definitions in the literature that state their differences. For example, in the work of Kooper et al. (2011), IT governance centers its attention on applications, infrastructure and on a more generalized view of IT assets. On the other side, data governance requires well-defined discrete knowledge as it focuses on data assets (Khatri & Brown, 2010).

Looking from the perspective of their joint technological nature, IT governance and data governance share some properties. Both IT and data governance are also considered subsections of corporate governance by some authors (Figure2). In particular, for Kooper et al. (2011) corporate governance is wide-ranging across all assets in an organization, while the span of IT and data governance is limited to specific types of assets. Given their very technically specific asset focus, they form coherent knowledge domains. Yet for some authors, more relevant is the data aspect of the governance and it attracted their research focus. Even in such work, characterizations of data governance as a set of processes within organisations detailing objectives, alongside a decision-making framework necessary to reach such objectives, is still very consistent with a similar definition that can be found in IT governance (Weill & Ross, 2004) and information governance research (Khatri & Brown, 2010).

Figure 2: Examples of the hierarchy of governance-related concepts



Source: Author

Even on the data level, a similar movement of attributing governance as a wider span all-embracing concept is seen. Governance underpins all data integration, risk management, business intelligence, and master data management activities consistently across an organization with a number of advantages over imposing inconsistent rigor to these projects and activities (Seiner, 2014). Consistent with that, Otto (2011a) sees it as a companywide framework for assigning decision-related rights and duties in order to be able to adequately handle data as a company asset.

There is a consensus among a group of scientists that perceive data governance as a means of extending enterprise-wide distribution of decisions, rights, and responsibility, further raising the importance of its extent or its span. Due to the prevalent use of information technology (IT) systems today, it is imperative that controls are in place to ensure the proper use of IT applications and to protect data from non-authorised change (Cheong & Chang, 2007). In addition, Weber et al. (2009) list mediums of data governance enforcement as the distribution of decision rights and voting powers, responsibility acceptance, synchronization, communication and conflict resolution amongst stakeholders.

Governance raises a flag for a specified organization-wide decision-making framework that, according to Weill and Ross (2004), contains some roles and needs to fulfill certain tasks and responsibilities to these roles. Moreover, accountability is essential to prevent a lack of clear ownership of data management and fewer errors will enter the system if there is the responsibility (Brackett, 2010). Data stewardship, which authors see as the operationalization of data governance and place where most of the day-to-day work of data governance gets done (Plotkin, 2013), is a concept for McGilvray (2008) primarily needs to formalize accountability.

Such clarity objectives, tasks, roles and responsibilities for multiple governance domains within its span comes from establishing core (data) principles as a higher order realm and source for guidelines in any of the subdomains, even technical ones such as data quality, metadata, data access and data lifecycle (Khatri & Brown, 2010). If seen as formalizing behavior around the definition, production, and usage of data in order to gain confidence which will improve the usability of selected data, then governance should aim to extend and make its span wider in order to make more data usable.

For Khatri and Brown (2010), data governance refers to the entirety of decision rights and responsibilities regarding the management of data assets. Choeng and Chang (2007) summarize various definitions of data governance. One example is as a holistic approach, focusing on people, processes, and technology to constantly quantify and measure their data metrics.

The process by which a company manages the quantity, consistency, usability, security, and availability of data with a major aim to exploit information as an enterprise resource is attributed to Newman and Logan (2006). Organizational bodies and rules for people as they perform information-related processes or the rules of engagement that management will follow as the organization uses data (Thomas 2006). If seen as primarily employing people, and processes besides technology, then this span of governance could go vertically (more people) and horizontally (more processes, which naturally adds more people).

Effective data governance has been suggested as critical in obtaining utility from centralized data use and data governance has been an emerging trend in enterprise-wide information management. It provides values to traditional information management with expanding its span, involvement, and alignment with business stakeholders, and cross-functional handling of data issues. Communication between departments (horizontal), and between management levels (vertical) is crucial in primary processes and workflows to improve the adaptability of data governance measures themselves (Orr, 1998).

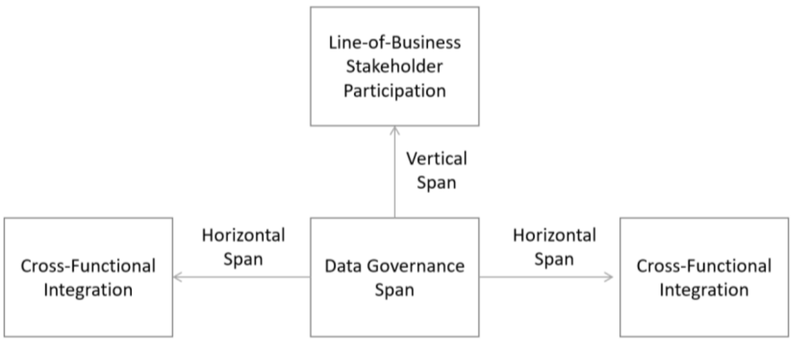
Furthermore, cross-functional and collaborative IT and business data governance processes need to be established especially as changing core data often means changing business processes (Delbaere & Ferreira, 2007). Therefore, the following two sections cover such horizontal and vertical span of governance. The one that focuses on the vertical span is line-of-business stakeholders' participation, and the other one emphasizing horizontal span is cross-functional integration.

As interpreted by Davenport and Short (1990), individual tasks and jobs change so fast that there is no point redesigning them. Rather than assigning the activity to one role, a team-oriented, coordinative, and communication-based work capability should be a carrier of such activity task outcome. It is not any more important to maximize the performance of an individual role or stand-alone business function - but to maximize interdependent activities that span across the company.

Based on an extensive review of the previous literature, data governance is defined in terms of two perspectives which lie along a continuum: narrowly and tactically as a particular technology solution, and wide-ranging referring to the value of its strategic utilization across the enterprise. Thus, this work develops a strategic framework that focuses on the span of data governance.

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 (Figure 3). First, firms need to vertically integrate and involve all business stakeholders. Second, they need to horizontally integrate and involve a wide range of departments. Taking all this together, data governance in a span context as a higher-order construct consists of two sub-dimensions: business stakeholders' span and cross-functional span. Each contributes to effective data governance implementation.

Figure 3: Directions of governance span



Source: Author

Research suggests that formal engagement which assumes their responsibility and formulation of objectives, evaluation of results and use of outputs are related to business stakeholders' involvement and helps firms to determine what actions to take. At the same time, the share of information and ideas between functions and cross-functional communication to resolve data issues are related to cross-functional span.

3.1.2. LINE-OF-BUSINESS STAKEHOLDERS' PARTICIPATION

The following section involves an overview of line-of-business stakeholders' participation, as one of two dimensions of its higher order construct - data governance span. This relates to its vertical spread and integration, which would be detailed as stakeholders' formal engagement. Formal engagement assumes their responsibility and enrollment in the formulation of objectives, evaluation of results and use of outputs.

The idea that data governance requires more attention from stakeholders has existed since the concept commenced (Alhassan et al., 2016), although initially associated with program sponsorship. At the highest level of data governance, the executive sponsor provides the necessary involvement from top management and thus enables the data governance program to be established throughout the organization (Wende, 2007). This chapter covers another relation to the business stakeholders. Line-of-business users of information systems are a vital source of a considerable amount of necessary system information, due to their knowledge of the nature of the work that the system is supposed to support (Hendry, 2008).

The stakeholder concept comes from strategic management and is utilized in the areas of project and portfolio management. A stakeholder is any individual or group who can affect or is affected by a project as elaborated by Vrhovec et al. (2015), and different stakeholders have their own different views. In order to get vital process expertise, business stakeholders must be established as information owners. Evidence of that can be seen in the fact that data decisions are often escalated in business, even to the executive level of an organization (Seiner, 2014).

Users typically have significant knowledge of the application domain, the tasks they perform, work practices, the context of the system use and their behavior and preferences. This form of knowledge is often tacit in nature and thus difficult to be articulated with typical elicitation techniques (Bano & Zowghi, 2015). Villar (2009) states that for business representatives their role must in the center of the governance model as critical data should be assigned to those who can apply business judgments.

The line of business stakeholders' participation can be also seen as part of a wider research domain of IT – business alignment - that has a high association with financial performance. The alignment of IT and business strategies generate a sustainable competitive advantage and increase profitability (Kearns & Lederer, 2003). Correspondingly, Ravishankar et al. (2011) suggest that if there is no alignment between IT and business, IT initiatives usually fail, there are wasted resources, all heading towards negative financial and organizational outcomes.

This concept of line-of-business stakeholders' participation has been incorporated in literature as an important characteristic of other similar enterprise-wide data initiatives with the potential to increase its span and therefore success. One such initiative that has been around for years is Master Data Management (MDM). Beside transactional data and historical data, there is a third category of data - master data - with the objective to consolidate major characteristics of cross-functional data entities such as customers, products, employees, and suppliers. Most of the time, master data is created once, used many times, without frequent considerable change (Knolmayer & Röthlin, 2006). MDM mandates identification of a primary business owner for every master data item and domain according to Smith (2008), and stakeholders must be engaged in the MDM initiatives. If they are not part of the MDM assignment of ownership, practice proves that even political problems are likely to arise.

Likewise, Silvola et al. (2011) argue that it is a challenging concept and must not be detached from general management practices in line-of-business. IT can maximally provide extensive analytical skills for the MDM work, however, to commence and sustain collaborative efforts and to determine what core processes are required is fundamentally a line-of-business problem, according to Flint et al. (2005). Its eventual objectives are to fix negative consequences from data fragmentation, stand-alone systems, rigid practices within line-of-businesses, inconsistent processes, and complex architectures. As such, MDM, therefore, needs to be a highly interactive social process (Vilminko-Heikkinen & Pekkola, 2017).

Similarly, the direction of the debate is in another body of knowledge of data quality discipline, which is very similar to both data governance and MDM. A major problem constantly stated in 'corporate data quality management' literature - is the lack of business involvement in the process (Wende, 2007). English (1999) explored critical success factors for sustainable information quality and discovered that some reasons for data cleansing initiatives failure are in lack of management understanding and active involvement. The quality of data used is important for the business as it is used exactly in line-of-business to support decisions. Lucas (2010) argues that ultimately the data quality issue is that, from its early stages has been seen only as an IT issue, while the purpose of data is to be used by the business.

Consistent with this is work from Otto (2011a) expressing that technical IT employees only concentrate on reactive data quality management activities, heavily underutilizing the potential that is in the data. If requirements for data standards, quality, and strategic alignment are undocumented and unstandardized, and if the business owners did not support the identification of data capture, maintenance, and usage process flaws that need to be mitigated, the information management initiative will not deliver results.

It is up to governance, as a newer discipline, to learn from such initiatives as MDM and data quality areas, and to contribute to the resolution of traditional challenges. It is seen as a concept that finally provides solutions in the work of representatives from business lines directly with representatives from a data governance team (Wende, 2007). Prior to the advancement that the data governance field provided, studies were failing to combine the technical and business-related aspects of data quality into integrated models, for instance.

The secret of the solution provided by the governance framework is that business and IT together document the corporate-wide data standards and policies brought up by governance management or management in its line of business. They create business rules for data, develop data vocabularies, maintain and publish data quality metrics, communicate their knowledge to each other and to management in charge, and recommend standards and policies. These line-of-business representatives are then proficient on how business processes use data and are masters of all business terminology in their area. Usually, they are assigned either per business unit, per major business processes or major data domains (Wende, 2007).

Research has already evidenced that companies need to pay extraordinary attention to processes in data management and to its governance in order for MDM to be successful (H. Smith, 2008). Under these circumstances, Andriole (2009) describes MDM as being part of technology, part governance, and even part philosophy. Conflicts or disagreements between project participants originate from differences in their goals, expectations, values, understandings, and realizations, as well as from lack of communication. If any of these factors get injected into meaningful intra-organizational dialogue by any means, there is evidence of the positive impact as a result of it (McLeod & MacDonell, 2011).

On the contrary, in environments with unclear criteria for decisions and with members with different goals, there is a long record of conflicts (Deutsch, 1969). It is usually a long-running challenge to get all stakeholders to agree, and therefore mechanisms such as governance framework are created to resolve ongoing conflicts. This allows the business to process critical decisions at all levels in a fast and pre-agreed way, which ends in a line of a consensus-building process and efforts across the enterprise.

In parallel, many of these types of framework elements are obviously driving user participation. Governance workflows provide granular management activity sequences of different processes and departments (Otto, 2011a). Furthermore, according to Ofner et al. (2012), workflow modeling (with embedding activities in it) - makes the creation and maintenance of these workflows important as practical 'user participation' driven activities that integrate data governance and quality into business processes of interest.

The context of information and data, as factors thought to be influencing the link between governance and line-of-business stakeholders, have been explored in several studies. Contextual explanation of data is a governance driven step towards alignment with business professionals that know, or would like to clarify, the meaning of data (Dahlberg & Nokkala, 2015). Data meaning and context reflect business policy, and hence a data governance program should be driven by the business, to control that data, and to define that ideal context where it should be used and determine who can access it (Wende, 2007).

Furthermore, there are authors that connect the concept with the ontological field. It is in principle based on a dictionary of terms formulated with commonly accepted definitions (ontologies). Hepp et al. (2007) outline that a dictionary should be developed and maintained in a community-driven manner, as this will drive user participation and collaboration. Correspondingly, Lillrank (2003) underlines that the data requires a context in order to state what it really means to have a certain level of quality, for instance. Wang (1998) provides an interesting analogy between producing information from data processing with regular product manufacturing.

Theories of Total Quality Management (TQM) provide methodology where the organization must clearly establish an information product team consisting of members who are information suppliers, manufacturers, and consumers (Juran & Feo, 2010). They all belong to the contextual area and processes of their line-of-businesses, and they will be able to articulate the information product in business terms.

Due to frequent misperceptions, it might be beneficial to comment on terminology and operational definitions discrepancies. There are "user participation", "user involvement" and even other terms, such as "user influence", that are frequently employed to identify the same construct. The idea of user involvement impacting information systems implementation success can be traced to organizational management research, including group problem solving, interpersonal communication and individual motivation (Bano & Zowghi, 2015). Swanson (1974) was one of first that emphasized the issue with lack of clarity on what is meant by involvement. Some authors covered the idea from information systems research whilst others did it from organizational behavior research. Barki and Hartwick (1989) support the idea that 'information systems involvement' construct should use "user participation" instead of "user involvement".

Alternatively, for Dubi and Champoux (1975), the term "user involvement" has a strong explanation, as a degree to which individuals even identify psychologically with their job and work. Consistent with this are Torkzadeh and Dwyer (1994), who says in a statement that user involvement is a component of organizational culture and therefore related positively to user satisfaction. A similar connection is made from Bano et al. (2017) who evidenced that organizational culture, user motivation, and complexity of the project are elements that impact the selection of appropriate user involvement strategy. This project will eventually use stakeholder participation as a better fitting term.

The category of project success is linked and embedded in some of the definitions of user participation. Determining the users that will engage in the project of information system application or development is an important factor (Bano & Zowghi, 2015), as not all of them will have the same implication out of its usage. Making the selection of users to engage from the set of stakeholders that might have potential to participate, is an important process that impacts the success or failure in effective user engagement as well as in the whole project success. Similarly, Ives and Olson (1984) defined user involvement as participation in the system development process by representatives of the target user group.

In literature, participation is associated often with responsibility as well as a channel to spread its span vertically within a governance program. For instance, to assess participation with individual responsibilities and influence, there are even measures developed by Baroudi et al. (1986). Likewise, Otto (2011a) states that data quality management in a cross-divisional environment suffers from the missing definition of clear organizational responsibilities on the line-of-business level.

Umar et al. (1999) provided results from a case study conducted in the telecommunications industry that confirmed the primary reasons for data quality issues is lack of roles and responsibilities and lack of data quality owners - which lead to inefficient organizational procedures in scheduling scenarios. Smith (2008) also outlines that one of the major problems is ownership issues in data quality projects. Lee (2010b) perceives information quality assessment barriers like lack of responsibility for information quality in business stakeholders, followed by lack of procedures.

Correspondingly, the literature on master data management (MDM) underlines that delegation of responsibilities for maintaining master data is the aspect which has the largest impact on master data success and a key challenge in identifying a primary business owner for each piece of data (H. Smith, 2008). Choices related to domains and valid values, data accessibility, timescales and actors, security policies, and the frequency of updates, demand that the ownership and the owner responsibilities must be explicit.

Responsibility for data management is mainly placed at the IT department according to Weber et al. (2009), while it logically does not make sense to hold a whole department accountable for wrong data entry or for incorrectly understanding data. IT plays a large role in ensuring that all required software and hardware is up and running while business should be responsible for the content and interpretation of data (Kooper et al., 2011). The cause for this is the connection that ownership has with responsibility. Uncertain data ownership might result in inadequate process definitions, making data maintenance problematic or even impossible (Silvola et al., 2011). Carefully selected attributes that explain data can help establish data ownership, usage rules and effective workflow (Leenheer, Christiaens, & Meersman, 2010). Often the starting point is the assumption that since IT owns the systems that store and maintain data, they also own the data.

Similarly, data ownership can easily be regarded as the IT unit's task as the data is eventually always associated with certain information systems and databases where it is stored. However, to understand the responsibilities of such an ownership role and map it with adequate process definitions, the data owner has to be found from the business processes (Silvola et al., 2011). Wende (2007) outlines the importance of historical experience in that if accountabilities are assigned to IT departments, the problem resolution will end up in the same department by simply implementing another technically oriented data management or data warehouse system.

Line-of-business user participation is connected by some authors with an effective change mechanism, one of the major governance values provided on the top of information management that promotes its further span. Jarvenpaa and Ives (1991) and Swanson (1974) associated it with participation in the frequency of initiated changes or queries utilizing from the side of business stakeholders. Similarly, in the research of Smith (2008), the focus group outlined business sponsorship, stakeholder involvement, and data stewards and change management specialists as key roles that need to be commenced in MDM work.

Several attempts have been made in the literature to associate user participation with governance in setting objectives and its evaluation, referring to it as a means to increase the vertical span of governance. Otto (2011a) notes that data quality management should participate in the design of the major goals of the initiative. The only way the business processes can operate with high-quality data is in the secret of data governance alignment with a business via objectives and its evaluation. They need to ensure that data meets the required quality standards set by carefully defining data elements and values (Wende, 2007). Only business professionals can say what data are needed to perform specific tasks and what the content of such data should be (Dahlberg & Nokkala, 2015). Hence, middle management will be formulating data objectives and evaluating results. They might take the attribute of 'ideal business stakeholders', considering their knowledge of operations in conjunction with their easy access to top management (Raes, 2011).

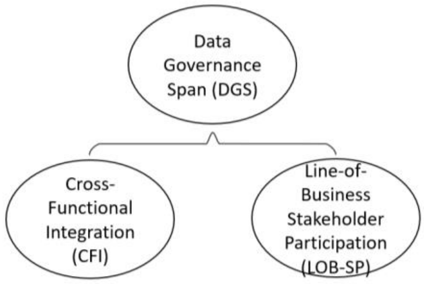
Moreover, Knolmayer and Rothlin (2006) state that management, in setting measures, should thus ensure that the importance of the relationship between business processes and data is evident to each and every party. Similarly, Vaygan et al. (2007) argue that without proper involvement of line-of-business stakeholders in setting and reviewing its measurement, master data do not have sufficient quality. Lastly, a survey by Haug et al. (2011) demonstrates that the vast majority believe that poor usage of measures for master data quality does have significant negative effects on its adaptation, its span across functions, and success of the whole initiative.

In order to understand the link between line-of-business participation and expansion of governance span, more recent attention has focused on the framework of collaboration and knowledge transfer - mandates that governance has 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). One of the ways to do so is to set up a system that encourages collaboration between business and IT people across the organization (Dreibelbis, 2008).

3.1.3. CROSS-FUNCTIONAL INTEGRATION

This section involves an overview of cross-functional integration, as one of two dimensions of its higher order construct - data governance span, relating to its horizontal spread and integration (Figure 4). It is conceptualized with several elements that would support its further operationalization: in horizontally well-integrated governance frameworks there is a share of information and ideas between functions and cross-functional communication to resolve data issues.

Figure 4: Higher and lower order constructs in the research model



Source: Author

It is already recognized as a continuous challenge that many information management initiatives just start and end within only one functional domain. Unfortunately, the initiatives do not even have a chance to touch the full cross-enterprise complexity across the business and IT environments. They could be characterized by a lack of horizontal span obviously. Governance is able to address that challenge with its clear and unambiguous understanding of data, that is vital for the effective management of multidivisional companies (Hüner, Otto, & Österle, 2011).

Seiner (2014) highlights that governance is a practical and effective initiative that serves well the promotion of data as a cross-organization asset. A key aspect of governance is denoting common terms and definitions that are used across business units. For the selected set of critical data elements, data governance provides controls over the data definition, data production and data usage across the whole enterprise where information policy and change is owned by a cross-functional authority.

Galbraith (1974) concludes that even if organizational hierarchies are designed in a way that the most interdependent units are linked, this is not sufficient if a formalized, standardized language does not support the protocol of large amounts of information between subunits. Likewise, smooth and effective business process execution that spans across multiple functions is ensured by a well-defined explanation of the data structure (i.e. their attributes and relations) and correct usage of these explanations and objects in business processes (Hüner et al., 2011).

There is a consensus among a group of scientists that cross-functional integration and growth of the horizontal span of governance is important for its ultimate mandate and successful outcome. In strategic management, the roots of an integration concept originate from Fayol (1949) and his notions of cooperation and coordination, and from Lawrence and Lorsch (1967) in the process of united efforts from various subsystems as an eventual goal to accomplish an organization's tasks. Integration reflects how harmoniously the different line-of-businesses work alongside each other and what the level of their coordination is.

Strategy literature has used the concept of integration to describe the management of the dependencies and coordination of activities. Some authors describe the intersection between integration and use of cross-functional teams. For example, Pimenta et al. (2016) define it as sharing general objectives, alignment of functional goals, the interdependence between tasks and common problem-solving influencing communication and collaboration.

Data governance efforts always begin within a single domain setting, whether it be a functional or systems setting. Respecting gained quick values within a single function or domain, still, the level of reach across the overall holistic data management ecosystem and across the business and IT environments are initially under-staged. The issue is that it does not fix problematic data flowing in from the multitude of source systems filling the governed system, application or domain that is beyond initial governance reach. There is a considerable amount of impacts and dependencies that other upstream or downstream applications and users may have on that single governed island of information.

Extending its horizontal span is the only option. Data governance develops an additional tier of data explanations, above all functional islands and their sub-standard. This tier becomes shared, flexible and therefore more easily approachable from different domains. Over time the tier is able to provide trust in data through a hardly achievable consistency on how each piece of key data is created and changed since the creation. All its deviations are captured by a process that sustains it as a living specification of the change. The tier will only make sense and value if all of the stakeholders from the domains across functional areas are engaged and active (Leenheer et al., 2010). Governed domains start to follow the same standards and the amount of transaction flows between departments is related positively to the degree of domain similarity between them (Ruekert & Walker, 1987).

There are more ways to horizontally extend span across different domains: systems, projects, subject areas, and processes. Selection of these domains can be approached from different directions. Some organizations start at the highest level and break domains into subdomains, while others initialize a program from the bottom and from the operational issue that specifies a set of critical data in one starting domain (Seiner, 2014).

The focus of this research is cross-functional span (function as domain), which at the same time is the one that the most often intersects with a span over the system, projects, subject areas and especially processes. Dyche (2015) explains advantages of this approach, and in the model by functional areas, data stewards establish definitions and rules usually easily due to the clearly bounded scope and are very familiar with the data's context of usage. In the functional model user, engagement challenges are minimal as stewards work side by side with business users. In the process-oriented model, stewardship is seen as a natural extension of process definition and success measurement is more straightforward. Data metrics in the context of the business are easy-to-explain benefits of data governance.

One of the initial organization design innovations raised in the organization theory literature in the 1960s was horizontal linking mechanisms (Mintzberg, 1979). For Mintzberg, they are instruments motivating liaison of contacts between individuals in order to coordinate the work of two units. Galbraith (1974) also introduced a continuum of horizontal mechanisms based on their increasing ability to handle information. Horizontal human resource practices are also suggested by Porter (1998) as tools to expedite collaboration across business units for competitive advantage.

Achieving adequate vertical strategies, combined as well with horizontal strategies is a challenge for managers and both authors are in agreement with this (Galbraith & Lawler, 1993; M. Porter, 1998). Integration can be structural and non-structural, and the task for researchers is to develop useful ways to categorize them (Mintzberg, 1979). Horizontal mechanisms have been exploited for some time by IS managers in order to increase collaboration across IS units and at the same time across business units. Nadler et al. (1988) looked into organization design and root cases for patterns and concluded that, regardless if a hierarchical structure within the firm is centralized, decentralized or federal, drawbacks to cross-unit collaboration are still created by the firm's reporting regimes. This is what horizontal mechanisms can erase. Mechanisms can take the form of cross-functional teams and liaison roles (Zmud, Boynton, & Jacobs, 1986). Finally, implementation of a horizontal mechanism is also seen as a strategy to address a challenging governance objective to increase its span and govern its efforts across multiple systems development units (DeSanctis & Jackson, 2015).

Another direction of theoretical roots can be derived from ontology engineering theories. Methods and tools are designed to support a decentralized group of stakeholders in the sense of geographical dispersion, varying levels of skills, experience, and responsibilities. As well, potentially divergent agendas to reach a consensus in an incremental and asynchronous fashion are found in ontology engineering theories (Holsapple & Joshi, 2002). These supported elements are building blocks of data governance at the same time.

It is not recommended to blindly apply a horizontal linking mechanism and work from some authors raises caution. King (1983) records that it is true that local self-sufficiency over the design of systems challenges the process of gathering of data for upward reporting and some level of integration is needed, while on the other hand forcing the organization-wide standards cuts departmental autonomy. Ashok Gupta et al. (1986) claim that the benefits of resource sharing between strategic business units are not without costs. Departments may need the flexibility to change their information systems locally and autonomously in order to resolve locally specific event challenges in the most efficient way (Michael Tushman & Nadler, 1978). Likewise, for Sheth and Larson (1990) loss of local autonomy might also mean the loss of local effectiveness to deal with integral within-unit task complexity.

Resolution is in the domain of governance. A central authority with control over the logical-only aspects of data in terms of organization-wide data integration is a solution good enough to balance it out (Heimbigner & McLeod, 1985). In its practice, it supports the idea that in the design of optimal level of cross-functional integration on the data level there is a need for trade-offs between organization-wide coordination against increased local flexibility and local effectiveness.

Literature has emerged that offers the proposition that cross-functional span of governance is related to the sharing of information. In governance framework, formal allocation of general decision rights and resources are to be supplemented with additional information sharing methods and coordination of IT tasks across multiple organizational units (C. Brown, 1999; Winkler, 2012). This intersection of the structural organization enables horizontal, not just vertical, information sharing (Daft, 1989). There is a need for a more advanced level of coordination in a complex organization, with remote allocations of decisions and constant information sharing, as many parties are involved in decision making and execution (Peterson, O'Callaghan, & Ribbers, 2000). Dale et al. (1992) and Simon (1973) suggest the simple rise of a mass of data is not by itself an adequate and enough reason for gathering it into a unified and consolidated information system. The major advantage of a still single comprehensive system is in its capacity to share information across many divisions or functions or units of the organization. The need for sharing information is greatest where there are activities and procedures across those units that are codependent and where the actions of one subunit affect the results of another subunit (McCann & Ferry, 1979).

Several attempts have been made to link cross-functional span of governance with collaboration, communication and mutual resolution of data issues. Friedman (2007a) argues that cross-functional adoption of data governance increases the ability to manage data issues enterprise-wide and to have smother resolution and cross-departmental monitoring. For instance, a tier of governance driven data explanations makes sure that every one relevant receives proper and timely notification (Leenheer et al., 2010). These define enterprise data issues as cross-functional. Data are mainly attributed and explained using line-of-business based standards, or software application specific standards. Leenheer et al. (2010) further elaborate that such set of attributes are not the result of an agreement across the whole organization. Acceptance of shared responsibility for preventing data quality lapses and for answering the call to mitigate the associated data related business risks when they occur requires cross-functional, enterprise-wide initiative if all roles, regardless of their primary role or job function, need to be involved (Harris, 2011).

The actions of separate subunits in an organization can be coordinated using a number of different approaches. Data governance makes known and clarifies the business value of the organization's data but also unveils the communication and collaboration necessary to achieve that value. A governance group reaches agreement on a common view upon a domain of interest; and upon the structure of their shared knowledge in terms of concepts, attributes, relationships, and constraints. This group of stakeholders starts to have a straightforward consensus-building process.

Metadata, or data about data, is the governance concept. Huner et al. (2011) record the positive effect of collaboration on metadata and on increasing the quality of understandability and unambiguity of the whereabouts of a certain meaning in a certain context. This has reversed the effect that high-quality content as an outcome of a collaborative process might motivate individuals to increase their contribution, as the contribution of others is realized.

However, cross-functional integration and span increase are challenging decisions with their own trade-offs, as stated by some authors. Tools like rotating employees between departments might bring modest increases in information processing. However, they are at best - a simple mechanism with low implementation costs. More costly is the assignment of formal roles responsible for collaboration across different departments within an organization. The most excessive solutions are formal groups for momentary or continuing problem-solving, ad hoc task forces or lasting teams that have delegates from multiple units (C. Brown, 1999). These formal groups can be cross-functional teams built from a set of individuals from diverse functional specializations within the organization (Simsarian Webber, 2002), where these members are also members of other teams and have reporting relationships to functional managers as well as cross-functional team leaders (R. Ford & Randolph, 2016).

Zolin et al. (2004) argue that a particular value for governance is obvious from three major characteristics of cross-functional teams: diversity of specialization, high levels of interdependence and mutual accountability. Shared meanings and context alignment within one central place increases enterprise interoperability. If this central place is a community of gathered stakeholders in the form of a cross-functional governance team, interoperability will be given (Leenheer et al., 2010). The design of data governance structure needs to be carefully performed, to trigger participation from all levels of the organization, to efficiently expedite conflict resolution and to encourage the support from all relevant stakeholders in the organization (Cheong & Chang, 2007).

However, with the aim to increase organizational effectiveness, usage of cross-functional teams increases within many types of firms (Simsarian Webber, 2002). At the same time, Jackson et al. (1995) describe that teams are constantly transforming into more specialized and more diverse teams due to changing personnel and as new designs in organizational structures emerge. Henke (1993) states that cross-functional teams bring four major benefits: the inadequacies of hierarchical structures are neutralized by the skills of the teams in crossing the vertical lines of authority, the decision-making is decentralized, the overhead of hierarchical information is drastically reduced, and high-quality decisions often occur through the use of such teams.

In order to increase cross-functional integration and span of governance, it is not enough that more functions participate and assign their members to the team. They must also prioritize their stewardship mandate over the functional mandate. Factors significant to the success of cross-functional teams are that teams have members and supporters who highly prioritize the project, are task-oriented with pressure on fulfilling goals, and members are informed, supported and recognized (Proehl, 1996). Cross-functional teams can be seen as expert teams or task teams where members representing multiple organizational functions are primary there to integrate data expertise from those functions rather than serve as standalone objectives of functions (Denison, Hart, & Kahn, 1996). The knowledge of the domains that they represent makes members valuable.

To increase the summarized value of community it is implied that all functions need to provide a delegate, from the order management department, customer service, sales operations, finance, ensuring that usable data from that exact function are shared across (Krensky, 2014). With the addition of cross-functional governance teams, governance matures in its horizontal integration and provides structural integration mechanisms as well as procedural ones. Procedural mechanisms are specified rules and standard practices for decision making and alignment between business and IT units (Peterson et al., 2000). System change requests and service level management procedures are some examples. Van Grembergen (2004) names formal roles that link across different organizational units as structural mechanisms if they are permanent standing groups, reporting to the central team, not to their functions.

3.1.4. DATA GOVERNANCE ORGANIZATIONAL NATURE AND GOVERNANCE TEAM OF STEWARDS

In the last part of the previous section, the need for governance cross-functional teams is introduced as an organizational measure to extend governance span. In this section, the team will be rationalized as the team of data governance stewards. Additionally, this section covers extensive organizational exposure of governance.

The literature clearly highlights that organizational issues are more important to the success of data governance, rather than the technical ones (Wende, 2007). Its organizational tie is in the heart of the fact that governance stands out compared to previous holistic initiatives (master data management, data quality). Assigning decision rights within enterprises goes beyond the usual information system (IS) related activities and is a typical organizational task (Galbraith, 1974). There is an overall agreement in both the practitioners and researchers communities that establishing data governance is an organizational design task (Y. Lee, 2010a). Therefore, the data governance strategy must not forget to include the critically important concerns of defining organizational structures and job roles responsible for monitoring and enforcing compliance with the policies and standards throughout the organization (Berson & Dubov, 2011).

IS research also has already produced an aggregate of knowledge about the division of labor of the information technology (IT) function, the teams derived from it and consequent organizational forms. For instance, Brown and Magili (1994) transferred the principles of contingency theory to the organization of the IS/IT. The centralized, decentralized and hybrid organization had their own representations in various studies (C. Brown, 1997). This was followed by different organizational prototypes of data governance in certain individual cases (Otto, 2011b). Researchers already produced functional diagrams linking decision rights to appropriate roles (Weber et al., 2009). They gave a specification of roles such as data owners or data stewards, detailing data decision rights (Otto, 2011b).

Organizational theorists were searching for a design tool to establish a high degree of cross-unit collaboration and often the mechanism for implementation were matrix structures where roles have two reporting lines. This was proved successful as a reinforcement strategy for cross-unit accountability (C. Brown, 1999). However, in the setup with a high level of accountability, there is still a problem that common agreement between different domains is not always achievable, as members of the domain group will still be influenced by their own domain. That is the reason why methodology, workflow, and process are necessary to complement the structural organizational mechanism in the matrix, which is not sufficient on its own. The workflow and active process will keep domain members in constant interaction with the central tier, as well as amongst themselves (Leenheer et al., 2010). This is evidence of the governance contribution to the success of such structural or procedural mechanisms, that were previously failing in similar enterprise-wide initiatives.

Data stewardship can be derived from the stewardship theory of management and seen as contrary to the agency theory, where employees are generally believed to be mainly self-interested(Davis, Schoorman, & Donaldson, 1997). There are definitions of data stewardship referring to its operationalization of data governance. Data stewardship connects heterogeneous information, ensures common, meaningful data across applications and systems (Khatri & Brown, 2010). It is clearly an operational aspect of data governance (McGilvray, 2008), where most of the day-to-day work of data gets done (Plotkin, 2013). Data stewards act as the point of contact for data-related issues, arbitrate and mediate conversations between business and IT, and work across enterprise departments and domains to promote data exchange (Seiner, 2014). For Rosenbaum (2010), stewardship is a model of the creation of data-sharing arrangements that promote proper, safe, secure and ethical use of information.

The attention of some authors has focused on relating stewardship to the concepts of accountability and responsibility. It is a willingness to be accountable for a domain of business information for the welfare of the enterprise (Kooper et al., 2011). For McGilvray(2008) data stewardship primarily formalizes accountability. Since data is produced and used throughout the entire organization and since employees are dependent on the information of others, employees should be trained to feel accountable for data. Data stewardship is a concept with deep origins in the science and practice of data collection, sharing, and analysis intended to transmit responsibility to the data where data governance conceptualizes and carries out these responsibilities from stewardship (Rosenbaum, 2010). No matter how much people will feel responsible for business information, only having a dedicated group of specific data stewards will ensure consistent data management on a daily basis, without an alternative (English, 1999).

There is consensus in literature and stewardship is acknowledged as holding a crucial role in the execution of a data governance program (Seiner, 2014). Data stewardship is vital to the success of data governance (McGilvray, 2008). Some authors provide strong statements that without data stewardship it is impossible to get high-quality data (Lucas, 2010).

What is known about stewardship is partially is based on definitions from ontology engineering. Stewards must quickly obtain consensus on key business terms and review this consensus constantly across the organization. In ontology theories, there are fact-oriented methods (Halpin & Morgan, 2010), which are extended in data stewards' community-driven support and connected with data stewards' community evolution processes (Leenheer et al., 2010). Information management is practically connected with ontology. Fensel (2004) states that when used in information retrieval, information extraction, as well as data and process, integration ontologies provide reusable pieces of declarative knowledge which can be gathered into application systems in an economical fashion. Besides that, ontologies clearly define the concepts in a domain and the relationships between them, in the area of information science. According to Smith (2014), the definition of ontology is coherent knowledge representation - a dictionary of terms formulated with commonly accepted definitions - that different information systems communities can distribute and communicate. This has an intersection with previously used definitions used for governance. For businesses to obtain good data governance, connection to the instances used in different domains is required (Spyns, Tang, & Meersman, 2008). However, it is necessary to follow the domain rules that contain constraints that every requestor-application must fulfill in order to try to interpret an ontology (Thomas R. Gruber, 1993). Once the discussion evolves, issues can be grouped and members are the editors implementing changes (Simperl & Luczak-Rösch, 2014).

Theories of communities are linked with data stewardship by some authors. This community of stakeholders is gathered together to understand the need to bring up and explain their own world of meaning, context, and explanations of data, and apply all this in interoperability requirements (Leenheer et al., 2010). Sociologists, social psychologists, and anthropologists explain in detail the concept of community (Barry Wellman, 1982). The community is a social network of relationships with a strong sense of sociability support and sense of belonging. It is a set of relationships where people interact socially for mutual benefit (B. Wellman, 2001). Social goals, social workflows, organizational structures, and social norms exist as constructs in this. It is a socio-technical system.

For Preece at al. (2005) social policies, understandable and acceptable to members, that support the community's purpose are to be nurtured and developed to achieve the success of the community. The strength and nature of relationships between individuals are what defines community more than physical proximity (Preece & Maloney-Krichmar, 2005). An example can be seen in the way how Rheingold (1993) defines intense feelings of camaraderie, empathy, and support among people in online communities. Preece et al. (2005) show evidence that the ties of a community come with the access that two persons have to each other, the group's capacity to communicate, the stress on normative obligations, the possession of resources by network members, and the similarity of members that drives empathies.

Literature related to ontology engineering and data stewardship can be integrated with community-related literature. The teachable and repeatable methodology requires a community-driven system for business semantics management (Spyns et al., 2008). A model theory inspired by ontology engineering methodology and community-based ontology is based on social interactions between people, interactions of these people and the information systems that support them, and the ontologies (meanings) required to establish semantic interoperability between these systems. Members of collaborative teams exceed in their achievements on the waves of motivation that come from working towards the shared and united purpose amongst other members (Harris, 2011). Each of the involved activities in the ontology evolution methodology requires certain skills and tools that domain experts usually lack. Finding a community and social arrangement of these roles and responsibilities is a supreme motivator compared to the value of the implementation of any methods and tools. Consequently, it is necessary to keep a record of actions, discussions, changes, and progress of concept domains, to see properties and the relations between them, in order to shape such roles and responsibilities also into a socially optimal arrangement. (Hepp et al., 2007).

Different governance roles have been identified in the literature (Korhonen et al., 2013). However, the terminology used in practice is complex and requires clarification. Wende (2007) mentions five roles: data governance executive sponsor, data governance council, chief steward, business data steward, and technical steward. A data governance council often assigns the data governance stewards, with the consideration for the existing workload carried by the individual selected (Seiner, 2014). Fully governed data would mean that there are roles associated with critical data domains and for data elements that constitute such domains: data governor or data owner and business data steward are names used often for the roles. The term data owner explicitly reflects mainly to the concept of accountability (Talburt & Zhou, 2015). A proposed change to any of the items may have to be authorized by several roles (Plotkin, 2013). Berson and Dubov (2011) notice that practitioners often call for the importance of distinguishing between data owners and data steward. Otto (2011b) provides this clarification, that data owners hold accountability for immediately correcting and provide consistency of certain data, while data stewards are accountable for the overall data management and develop and provide the rules for the handling of the data.

The term chief steward exists as well and is usually referred to as stewards' team leader, a coordinator in non-mature governance organizational structures. The role of the chief steward is to put the board's decisions into practice and supervise data stewards and to help them to enforce their mandates (Wende, 2007). Data steward as a term is in practice sometimes used for a wider group of roles with important tasks over data, although these roles remain within their respective project, process, functional, systems reporting lines.

Then there are the terms 'domain data steward' and 'business data steward' that usually exist in such a setup to distinguish a selected group of individuals which have characteristics of the formal cross-functional team. There are several definitions of these two roles. A business data steward is a key representative in a specific business area - responsible for the quality, use, and meaning of that data in the organization (Plotkin, 2013). Domain data steward is a role with a wider range, from having the authority to break the ties between operational units and participate or advise with management in decision making to the point that they are just facilitators in setting standards and resolving issues across functional and domain areas, leaving decision-making up to arbiters (Seiner, 2014). Some enterprises even have a data steward coordinator as the name for a business unit or functional area responsible for coordinating the activities of the operational data stewards in their units or areas which places this role in the center of data governance communications.

For the purpose of simplification and clarity in this project, only a single term will be used that contains the word steward – data governance steward. It is derived from the combined previous definitions of domain data stewards, business data stewards and data steward coordinators. It refers to assigned individuals that communicate changes to data policy, regulations, and rules to their units or areas and that develop rules for handling data. They formally belong to the cross-functional governance team. Although their reporting lines sometimes remain in their functions, they have another formal link that defines them as members of the cross-functional team. Those that have some level of responsibility for the data they define, produce and use during data entry, data integration and data analysis will be named operational data stakeholders in this project.

By default, operational data stewards do not govern themselves (Seiner, 2014). This group can belong to line-of-business, function, process, management, and have formal or informal, but obvious, ownership of data or they just participate in one of the important processes of data. Line-of-business stakeholders, mentioned in the previous chapter, would belong to this group. All IT technical roles would be also operational data stakeholders, except if they have formal responsibility for the governance domain. This is explained by Wende (2007) who states that business data stewards (or data governance stewards in this research) operate with the business representatives and are accountable for assessing the impact of new business requirements on data quality. However, a technical data steward might be appointed either per business unit or department or per IT and focus on technical metadata, profiling source system details and data flows between systems.

This is consistent with categorization in other fields of data governance research. For instance, in ontology engineering theories, knowledge engineers (KEs) or IT members, even having through expertise in the modeling, still come with the bias of their individual conceptions of the domain. The core domain experts (CDEs) from the business layer are recognized authorities who have an excellent overview of the relevant topics and players in the domain. The domain experts (DEs) form the majority of knowledge workers in the community. These are the professionals representing specific stakeholder interests (Leenheer et al., 2010). KEs are operational data stakeholders belonging to the IT department, or even to the data governance team. CDEs are operational data stakeholders and line-of-business stakeholders as defined in the previous chapter. DEs are data governance stewards.

Generally, the concept of data governance steward as previously defined is consistent with the moderator term in ontology engineering. The participants in an ontology engineering discussion choose a moderator. The basic rules for moderation also apply in this case: the moderator structures the discussion and organizes the decision process. When chance requests arise, they are allowed to decide on the deployment of changes to the consensual ontology model as a group of lead editors (Simperl & Luczak-Rösch, 2014).

In practice, there are several stewardship models that follow the concept of data domain defined in the previous chapter: (i) By functional area: sales, marketing, distribution, finance, customer service. Data steward focuses on the data that a given organization or organizational function – in this case, the marketing department – uses. This can include customer data, campaign and promotions data, customer value and risk scores, and third-party data. It could also encompass product and financial data; (ii) By subject area: products, customers, financials, location; (iii) By business process: procurement, campaign, enrolment, sales; (iv) By systems: billing, CRM, inventory, financials; (v) By project: (Dyche, 2015). The basis is to form and engage a body of shared meanings from representatives of relevant functions, systems, projects or processes. The group will develop and maintain data explanation representation of their world, having in place workflow and process control as they will not easily reach agreements (Moor, Leenheer, & Meersman, 2006).

Organizations typically have more than one model in the matrix. Wende (2007) promotes the model of dual management of data, one steward for business and one for technology and sets these roles in a RACI table. Dyche (2015) elaborates on a combination of models where the common hybrid model is subject-by-function, where there may exist other data stewards for each subject area within functions or hybrid process-business-by-function combinations in which each business unit that has a stake in a given process has a data steward assigned to it. In this scenario, each process has multiple data stewards and a steward for a given business function may also represent multiple processes.

The focus of this research is governance span which can be horizontal cross-functional and vertical towards line-of-business stakeholders. Horizontal span is primarily ideally mapped in a model by functional areas, but should not be limited to this. However, functions are the ones that most often intersect with a span over the system, projects, subject areas and especially processes. Vertical span would follow any model of stewardship that reaches line-of-business stakeholders, which is more often the case with models by functions and by processes.

Development of a data governance program starts with reconsolidation and listing of data domains, data domain stewards, and enabling the domain stewards (or data governance stewards in this research), to successfully manage data across the enterprise (Seiner, 2014). Once a data governance steward is assigned either per business unit, per main business process or per main data type, for their area of responsibility they start to detail the corporate-wide standards and policies, whether self-initiated and approved by the data governance board or brought up by the board (Wende, 2007). Data governance stewards do not have to write all or many policies, but they must be aware of what policies have been written (Plotkin, 2013).

There are issues with identifying a domain data steward that are normally resolved with breaking the domain of data into multiple subdomains which brings a logical choice of visible domain data stewards. A data analyst or business analyst are often good candidates to be data governance stewards, as they already work very closely with data dimensioning. Most functional areas have people who work with data more than others, supervise, control, monitor and fix data in some way, while some of them have even a passion for the data (Plotkin, 2013). Their roles need to be formalized.

3.2. GOVERNANCE TEAM LEADERSHIP

This part of the theoretical background conceptualizes the Governance Team Leadership (GTL) in the context of governance project, organizational change, change resistance, the role of leadership in managing change and change resistance, transformational leadership in establishing team identity, communication and knowledge sharing.

3.2.1. GOVERNANCE PROJECT, ORGANIZATIONAL CHANGE, AND RESISTANCE

In this section the concept of change and resistance to change are raised as concerns in a model of data governance team – data governance stewards and on the way how they are approaching operational data stakeholders (including line-of-business stakeholders). In upcoming sections, such governance stewardship operating model, change management and managing resistance to change will be integrated with the leadership concept as necessary knowledge areas (Figure 5).

Figure 5: Governance Team Leadership - Theoretical integration of concepts

Source: Author

Data governance is complex, and large-scale project to undertake. Despite the growing importance of it as holistic information technology (IT) driven cross-organizational initiative and program, firms are not successful in its smooth adaptation as its successful implementation can be 'too transformational' and controversial. Major IT projects and programs with a large impact on the organization, for instance, IS-driven redesign of work processes, are traditionally at the same time most problematic in their concrete realization (Lorenzi & Riley, 2003). The original creators of the information system (IS) are distant and detached from social issues associated with systems implementation (Orlikowski, 2002). Success or failure of the initiative has historically been evaluated on an IT surface application usage basis while ignoring the organizational implications beneath (Orlikowski & Robey, 1991).

Data governance papers belong almost exclusively to the IS change management literature. Data governance programs follow primarily typical IS change management practice, and normally intensively detail just the technologic aspect of IS changes, often overlooking their organizational impact. The challenges of larger IT projects and programs are that IS changes are not coordinated with organizational changes. Such changes are more difficult because it is hard to manage and foresee the actual response of individuals and groups due to the complexity of affected relations in an organization (Vrhovec et al., 2015). Jenks (2012) states that the result of strong resistance is that after a period of instability, the practical result is a technology-centric organizationally isolated project with complete avoidance, which is often the case in reality with governance projects.

Data governance brings organizational change. Organizational change, by its very nature, threatens a person's comfort zone and spurs resistance (Krantz, 2016). Data governance is rarely spread across the enterprise all at once. It is gradually reconciled in specific business areas, divisions, units, or applications or some combination thereof. Governance is seen as the set of decisions that define expectations, grant power, verify performance, or a quality control discipline (Berson & Dubov, 2011). Regardless of their recognition that it is in the root of their data problems, many organizations still operate in silence and fear that an increase of governance span will come with pain, conflicts, political battles, differences of opinion and additional workload. Understandably then, data governance stewards experience a high level of resistance (Seiner, 2014). Resistance to change is caused by the change in job content as data governance implementation affects most of the company's business functions. This, in turn, influences the job content of the majority of users directly (Jiang, Muhanna, & Klein, 2000), declining their participation. A line-of-business stakeholder (operational data stakeholder) is affected by a project and is expected to raise resistance.

Contrarily, resistance to change by employees is continually listed as one of the most frequently encountered reasons for non-use of innovative projects (Jiang et al., 2000). Venkatesh et al. (2003b) provided evidence that an individual's determination to use innovation in the form of IS is impacted primarily by organizational contexts factors. Similarly, Kim (2009b) affirms that user resistance to information systems implementation is determined as a primary and outstanding reason for the failure of new systems generally, and hence needs to be understood and managed. Markus (1983) looks at resistance to IT implementation in terms of a power distribution misalignment that IS brings to existing informal setups. This political perspective definition appears to be particularly applicable for cross-functional information systems such as a governance program. The logic of opposition to organizational politics or organizational culture is in the root of resistance understanding.

3.2.2. CHANGE MANAGEMENT AND CHANGE RESISTANCE

Following the previous section where change and resistance to change are raised as concerns in a model of the data governance team, this section provides more details on change management and change resistance.

The information society requires that modern organizations transform and adapt persistently (Bovey & Hede, 2001). Fiedler (2010) argues that to be successful, a firm's general ability to change needs to be rapid and efficient. Those that can adapt quickly enough to the changing environment can be successful and survive in the long term; others cannot (Gareis, 2010).

There are several theoretical tracks when it comes to organization and change management. In institutional theory, organizations adapt naturally to the environment - and produce external legitimacy and support (Meyer & Rowan, 1977). Contingency theory focuses on internal effectiveness and that way adopts a strategy and forms the organizational structure (Donaldson, 1999). There is also the strategic choosing theory, where leadership and leaders (managers) are the real actors of the change process (Child, 1997). The latter is the best fit for the aim of this research.

The focus on the topic about organizational change started with studies on organizational flexibility (Sofer, 1964), and progressed towards change in centralization and change in power between departments in organizations. Later, it moved towards organizational development, and then the idea of active change agents took over primary focus in research. For example, Kimerly and Nielsen (1975) argue that actively changing employees' behavior and their perception of change are means for proceeding with organizational change. Harari and Zeira (1976) confirm that 'followers' participation' is a considerable influence factor in the change process.

Resistance to change and its management have again gained popularity in change management studies. Armenakis et al. (1999) suggest that simulations of organizational responses to induced change are recommended, as it almost always, and often for the first time, unveils the deeper cultural problems in an organization such as inertia and change resistance.

Resistance to change is frequently in definition referred as 'the enemy of change' (Waddell & Sohal, 1998), as a source of conflicts (Hultman, 1998), or as unexpected costs and delays. Weick and Quinn (1999) illustrate that 'change is something that people with power do to the powerless', where boundaries and success are maintained by the exercise of power. Many authors believe that resistance should be expected as a part of any change process (Pardo del Val & Martínez Fuentes, 2003; Proctor & Doukakis, 2003) as it emerges in order to keep the status quo in organizations (Henry, 1997). Change upsets the balance and leads to resistance as a natural response to it (Bovey & Hede, 2001). Resistance becomes more active as transformative action is set in motion. Per Anderson (2011), resisters 'lie in wait for the change to begin'. There is a point of view in the field that a change process that faced minimal resistance was well managed one. Oreg (2006) highlights the importance of differentiating between the two types of resistance: reactions to change outcomes and reactions to the change process.

Organizational psychology authors defined resistance to change as "the forces against change in work organizations" (Mullins & Cummings, 1999). It can also be defined as a user's opposition to an information system during the programs implementation and the behavioral expression of it

(Klaus & Blanton, 2017). Oreg (2003) argues that it is a personality trait, and Ford (2008) defines it as a set of roles that interact, where highlights need to distinguish between the change agent and change recipients, and especially their relationship. Lewin (2016) adds the concept of resistance to change within his field theory. Alternatively, Lapointe and Rivard (2005) look at resistance at the group level as a political variant of interaction theory from Markus (1983). Judson (1966) argues that individuals tend to join organizations for security, harmony, perception of their self-image, sense of worth, and goals, that is reflected in groups they belong to in the organization. Likewise, Michelstaedter (2004) suggest that people always look for consistency, routine, and a predictable agenda of activities and responsibilities. More organizational definitions are, for instance, from Eisenstat et al. (1990) who argue that resistance is a function of the fallacy of programmatic change, and from Kotter (1995), where resistance is the obstacle in the organization's structure. With a newer focus on individuals, Spreitzer and Quinn (2016) look for resistance explanation in individual characteristics, such as self-esteem, and in organizational characteristics, such as barriers to work. Lapointe and Rivard (2005) take behavior as the primary dimension of resistance, as a reaction to the situation perceived as being negative, as inequitable, as a threat, or as a stressful feeling. The user can express this behavior in an active form (visible and relatively easy to detect), or a passive form (harder to detect and difficult to deal with) (H. Kim, 2009a).

Factors that can influence resistance are pressure (Enns, Huff, & Higgins, 2000), uncertainty and the loss of status or power, perceived values or switching costs (H. Kim, 2009b). Anderson (2011) researches resistance and reveals that people's subjective assessment and sense-making of intensity, source, and focus is the foundation of resistance in practice. One source of resistance is the established culture of the prior administration. It can be an inherent culture of mistrust (Pfeffer, 2003). Status quo protection is a source of resistance and in turn affects the fundamental aspects of organizational life, working in the way one was trained, and being able to demonstrate expertise (Cameron, K. S., & Quinn, R. E., 2006).

Information systems research has identified resistance to change as a major reason for IT project failures and an especially strong factor in larger IT project failure (Aladwani, 2001; Lorenzi & Riley, 2003). The resistance of the human factor against change and effectiveness in organizational processes is outlined by some authors (Eisenstat et al., 1990). Laumer (2011) summarizes that IS denotes concepts of resistance to change from managerial psychology research. It is covered in literature as a function of political resistance to change, cultural resistance to change, institutional resistance to change, and resistance of existing organizational memory to change (Boudreau & Robey, 1999).

Newer work is focused on employee psychological empowerment (Lorinkova & Perry, 2013) and engagement and psychological contract fulfillment (van den Heuvel et al., 2016). Resistance is addressed by combining the practice of change management and project management (Pádár et al., 2017), organization culture adjustment prior to the change (Paro & Gerolamo, 2017), leader-follower mechanisms (Bakari et al., 2017), and employee perceptions of leadership influence (Caulfield & Senger, 2017).

3.2.3. LEADERSHIP AND MANAGING GOVERNANCE CHANGE AND RESISTANCE

In this section, the concept of leadership will be added into the operational model of the data governance team – data governance stewards. It will address how they are approaching operational data stakeholders (including line-of-business stakeholders) due to several needs, including change management and managing change resistance.

Change agent, program agent or leader is a term referring to the data governance stewardship team or its member, while follower or rester refers to the line-of-business stakeholders (operational data stakeholders). Vrhovece et al. (2015) even use stakeholder resistance as a term to combine user and organizational resistance. The concept of divisional or functional resistance, as described by Markus (1983), can be applied as line-of-business resistance for the purpose of this project, while the concept of user resistance from Kim (2009b) can be adopted as line-of-business stakeholders resistance.

Much of what is known about managing resistance to change is theoretical, from works from Hultman (1998) and Judson (1966), and literature-based theories struggle to properly operationalize the construct (Karl Weick, 1976). Reactions to resistance are improvisational and not systematic at all; neither is rational. Unfortunately, in practice, the most common managers' response to resistance is passivity and overlooking the issue. When they respond to it, responses are often not strategically thought out and are ineffective. Authoritative persuasion as a default practice, however, does not solve the underlying root causes (van Offenbeek, Boonstra, & Seo, 2013). Additional complexity is the fact that it is insufficient to focus only on software users and pay little attention to other roles that may be significantly contributing to resistance or even resisting themselves (Markus, 1983). The information technologies create a complex framework for structuring working operations and support the different roles and re-model their efforts in the process of the introduced change concept. The influence of all these roles is critical.

It is often necessary to take a mix of several different strategies to reduce resistance and emerging conflicts. There are many different attitudes expressing resistance to change, starting from psychological ones and ending with technical ones. Effective management of resistance should utilize several scientific fields' bodies of knowledge. For instance, one might look at change management and project management, then analyze the complex dynamics of the behavior of the change agent, project manager, project or change sponsor roles from both sciences (Pádár, Pataki, & Sebestyén, 2017).

Luckily, planned engagement with resisters is much more systematic than just reactions to resistance. No single resource is more vital than proactivity and leadership for the planned transformation (Mhatre, 2014). Levay (2010) supports this by stating that leaders that display immense self-confidence convince their followers to trust in the leader's judgment. Likewise, Dent and Goldberg (2016) argue that resistance to change rises with the number of changes necessary to be processed and it must be neutralized by leaders of the change. There is also empirical evidence, for instance, where employee perceptions of leadership are a mediator for perceptions of change and work engagement (Caulfield & Senger, 2017).

The data governance stewards are necessary leaders. Their leadership profile is necessary in order to translate business strategy into data tactics to achieve the business objectives required. They are impacted by high requirements on collaborating skills and ability to influence both business and technology teams across business units (Villar, 2009). Jenks (2012) created a study where a description of the dynamics of resistance to a data warehousing initiative, a type of IT cross-organization program similar to governance, linking it to the distribution of organizational power. Data governance stewards will never have enough authority that will ensure their power - and have to rely on their own leadership capabilities.

In the last decades, scholars eventually concentrated on the topics of leadership when it comes to change management. For Nadler et al. (1990), the leader is crucial for the fast execution of the change process. Burke and Litwin (1992) specified that transformational and transactional aspects of the change, similarly as transformational and transactional types of leaders, were related to successful change result. Actual usage of leadership style is a key factor in organizational change management (Skinner, 2004). Authentic leaders are necessary for effective change management. They need to create readiness for change which in the next phase develops into their commitment to change and behavior that supports the change (Bakari, Hunjra, & Niazi, 2017).

Following the need for leadership addressing change management resistance, two concepts were taken that intersect with leadership theory - building team identity, and knowledge sharing and communication. This is just a small subset of potential behavioral or influence driven leadership strategies. Yukl (2013) argues that personal characteristics, situational/contingency factors, leader behavior, and power/influence contribute to the effectiveness of a leader. In this study, we focus on the last two sources of the team leader's effectiveness: power/influence via emission of strong cross-functional team identity, and transformational leadership and behavior via communication and knowledge sharing.

3.2.4. CROSS-FUNCTIONAL TEAM IDENTITY AND TRANSFORMATIONAL LEADERSHIP

Following the need for leadership addressing change management resistance, two concepts were taken that intersect with leadership theory - building team identity and knowledge sharing and communication. This section integrates theories of transformational leadership with the concept of team identity. Data governance stewardship team members need to have high team identity and some the transformational leadership abilities for an efficient span of governance, considering change resistance in such projects.

Cross-functional team identity of the data governance stewards is selected as a category with an influence on their perception from operational data stakeholders. It is also a category of influence in an overall increase of the span. If leaders or team members stand in positive relationships with other teams and their leaders, the whole cross-functional team is perceived positively outside the team. This adds to the identity for the team - the 'shining' identity will further enhance positive relationships (Simsarian Webber, 2002). The increase of the collective identity in employee self-concepts increases collective efficiency (Dutton, Dukerich, & Harquail, 1994).

The role of the team leader of the data governance stewardship team is important due to more than one, and often conflicting, reporting relationships in a cross-functional setup. Managing these relationships with functional managers and mediating between the functional managers and requires strong leadership abilities, both from the leader of the governance team and from stewards individually (R. Ford & Randolph, 2016). The leadership of the team manager in the process of creating a team identity is not the primary research target in this study, although many of considerations in this section could have been applied to a team manager such as the data governance stewardship team relationship. The primary relationship that this research is focused on is data governance stewardship team – operational data stakeholders.

Several attempts have been made in the literature to relate transformational leadership with strategies for addressing resistance. A leader positively impacts resisters of perceptions of performance, effort and social influence expectancy (Venkatesh, Morris, Davis, & Davis, 2003a), by sending strong motivational messages and modeling higher-order values. This stimulates a follower's personal identification towards the leader and shifts their social identification towards the collective (Neufeld, Dong, & Higgins, 2007). On the other side, the change leader muşt have that extra leadership quality, since now more businesses operate in an international setting, with teams and members very distanced and with very diverse cultures. Therefore, the change leader needs to be the one with impressive leadership qualities, be transformational, and utilizing every piece for the success of the change process.

Some newer approaches in literature propose that there are four dimensions that make up transformational leadership. Aga et al. (2016) suggest: Idealized influence as initiating persuasive follower emotions and identification with the leader; Inspirational motivation as articulating an appealing and inspiring vision, followed by increased expectations from followers; Intellectual stimulation as shedding light on awareness of problems with triggering innovative and/or creative approaches to solving them; Individualized consideration as support, encouragement, and coaching to followers. A transformational leadership style is more appropriate when the aim is to instill a culture of innovation (Sethibe & Steyn, 2015), and in that way manage resistance.

Strong team identity is already defined as 'superordinate identity' in some studies and described as the degree to which members identify themselves with the cross-functional team and success of the team (Miller & Brewer, 1984). Utilization of superordinate goals boosts cooperation between culturally different groups (Sherif, 1988). Pinto et al. (1993) showed that successful cross-functional teams enter into valuable communication, cooperation, and coordination team processes in order to be successful.

Strong functional identities are an integral part of an individual's self-concept (Tajfel, 1982). People normally act in ways that enhance (or make them feel good about) their self-concept, leading to underestimating comparisons of their functional area with others (Ashforth & Mael, 1989). Maltz and Kohli (2000) describe that there is a self-concept driven motivation for members to share information, to carefully pay attention to each other's perspectives during decision-making, and to be constructive in dialogs. Moreover, working effectively around organizational routines such team motivation can increase the likelihood of generating new ideas and innovation, making them acceptable to the firm (Deborah Dougherty, 1990).

A follower desires to maintain a high-quality relationship with an attractive leader (Shamir & Howell, 1999). Data governance stewards' transformational leadership abilities and superordinate identities will be passed to the followers or resisters – operational data stakeholders. This will allow them to start identifying themselves as a part of the same 'data' vision and extended part of strong cross-functional data governance stewardship team.

A large and growing body of literature has investigated transformational leadership relationships with the creation of identity. Choi (2016) names leaders as a cause of followers' identification with the vision, where actually their identification with leaders has a mediating impact in that relationship. Bono (2003) tested one of the most fundamental notions underlying transformational leadership theory and the self-concept based theory. This work showed that followers of transformational leaders find their work more meaningful. A first step in creating a purposeful organization is to personally build a life of meaning for yourself (Hacker & Roberts, 2004). This way, the strong identity of the governance stewardship team, based on their confidence and meaningful team values will emit and influence meaning to operational data stakeholders. This is supported in the literature. Even rewards fail to motivate resisters to pursue group goals if they lack a sense of ownership of the goals and the desire to accomplish something personally important (Richard M. Ryan, 1985) (Deci & Ryan, 1985).

Transformational leaders have the ability to link follower and work values and change self-identity (Klein & House, 1995). A leader who shows both self-confidence and deep personal concern for the well-being of resisters is likely to cause a strong sense of pride, commitment and meaningful duties feelings (Dionne, 2004). Thus, this increases the perception that their personal values are eventually similar to those of the organization. For Warrick (2011), this way the leader would not only make clear what needs to be done but be transformational, creating significant positive changes in individuals and motivating followers to switch their self-interests for a collective purpose. Followers with high levels of person-organization congruence perceive that they are a part of something bigger than themselves and are more likely to engage in behaviors that facilitate group productivity (Podsakoff, 2016). Levay (2010) records that a shift in the follower and resister mental focus from self-interest to collective interest led to a higher performance from followers.

Superordinate identity can be built from Organization-Based Self-Esteem (OBSE), as an individual's perception of their own value in the organization and the extent to which they are competent to act there (Pierce, 2016). Armenakis (2009) states that OBSE employees will interpret the change as an opportunity to seek learning and demonstrate their competence. Thus, and according to self-consistency theory and self-enhancement motivation, they will develop positive cognitions with respect to the change and their resistance will decline. Low. OBSE employees, in contrast, may comprehend change as a threatening process that will expose their lack of competencies, and according to the self-protection theory, they will protect themselves by avoiding participation in it (Hui & Lee, 2016).

3.2.5. COMMUNICATION AND KNOWLEDGE SHARING AND TRANSFORMATIONAL LEADERSHIP

Following the need for leadership addressing change management resistance, two concepts were taken that intersect with leadership theory - building team identity, and knowledge sharing and communication. This section integrates theories of leadership with the concept of knowledge sharing and learning through structure initiation. Data governance stewardship team members need to have clear proactive communication for an efficient span of governance, considering change resistance in such projects. McNulty (1962) indicated the significance of communication structure and managerial change in the change process. They would proactively pass on their knowledge in successful communication when they schedule work to be done, and organize, clarify and define the activities and maintain definite standards of performance.

Drucker (2002) marked that leaders willing and capable of communication are inhibitors of organizational change. Similarly, Sugarman (2001), argues that effective communication is crucial for the success of the organizational change process. The power of organizations and teams is not in the mythical figures of direction and influence (as the super leader) - but in the knowledge shared by all its members (La León de Barra et al., 2015).

In literature, there are already records of value from incorporating communication with knowledge sharing from an individual or group to another. This is the main subject of the Knowledge Management discipline (Alavi & Leidner, 2001). Knowledge sharing is the delivery of information to solve problems and develop ideas into cooperation with others (Cross & Cummings, 2004). Within the discipline exists even a subset of broad literature on the topic of data, information, and knowledge and their associations (Detlor, 2002). Studies reflect the idea that data are raw facts, information is processed data, and knowledge is detained, acceptable, and expressed information (Zins, 2007).

Detlor (2002) believes that knowledge is a set of justified beliefs based on individual and collective experiences. As a result of knowledge sharing, there is learning. Practitioners and academics have defined learning as a change in behavior resulting from actions/events or information/knowledge experiences (Narver & Slater, 1990). A considerable amount of literature has been published where learning is described as a fundamental capability/competence of the organization, as it facilitates the numerous business processes (George Day, 1994).

Learning is also associated with the detection and correction of errors (Argyris & Schön, 1978), which is relevant to governance frameworks. The same is explained in theoretical arguments from Madhava and Grover (1998) within the context of distributed knowledge and cognition in team management. Sarin and McDermott (2003) observe the effect of the team leader's behavior on team learning. According to Narver and Slater (1990), organizational learning orientation increases good practice between departments.

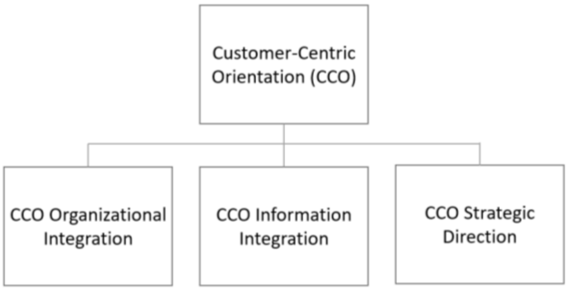
There are a number of published studies focused on the transformational leadership link to communication and knowledge transfer through work scheduling and structure initiation, and addressing change resistance. In the study of Aan (2016), significant findings were found in the relationship among resistance to change from one side and goal setting and critical communication from the other. Goal setting mediates the relationship between leadership style and works motivation, with transformational leaders able to set more challenging and more specific goals (Bronkhorst, Steijn, & Vermeeren, 2014). Goal communication in parallel with a compelling vision causes resisters to regard organizational goals as their own and submit extra effort toward their accomplishments (Shamir & Howell, 1999). Transformational leadership behaviors positively influence organizational innovation in goal setting environment (Prasad & Junni, 2016). One of the ways how knowledge sharing and learning can be operationalized is via the existing concept 'initiation of structure', defined as the degree to which the team leader assigns tasks and prescribes behaviours to the team members in order to achieve the desired results (Wofford & Liska, 1993). In the knowledge-based theory of firm of Grant (1996b), there are four mechanisms to adopt and integrate an individual's knowledge in organizations: to transpose tacit to explicit knowledge that can be understood by others by rules and policies, integration of knowledge by sequencing the order in which individuals interact, implementing a series of repeatable routine activities, and coordination of activities through joint, simultaneous interaction.

In addition, there is learning as a change in behavior resulting from actions/events or information/knowledge experience. The structure facilitates the creation of recurring communication patterns. Maltz and Kohli (2000) evidenced effective formal and informal communication as the most important factor to solve and prevent problems between two departments. Information systems should increase the speed of such communication to a great extent. The structure clearly and explicitly should state goals and task descriptions (Magpili & Pazos, 2018). Influencing team member behavior can be achieved via structuring the environment surrounding the task (T. Porter & Lilly, 1996). It reduces cases of dysfunctional communication and enhances conflict resolution in teams. Using structure initiation, team leaders are able to communicate individual and collective accountability. Sarin and McDermott (2003) argue that some inhibitors of collaboration between different functions are their incompatible goals and a lack of understanding of each other's roles. This is similar to the previous work of Ruekert and Walkor (1987), where initiation of structure improves communication and understanding among team members. The more complex and ambiguous tasks, the more important is structure initiation (Sarin & McDermott, 2003).

3.3. CUSTOMER-CENTRIC ORIENTATION

This part of the theoretical background conceptualizes the Customer-Centric Orientation (CCO) construct and its dimensions, customer-centric organizational integration, customer-centric information integration, and customer-centric strategic direction (Figure 6). Additionally, before the construct conceptualization material, the section covers customer-centricity and integration.

Figure 6: Dimensions of Customer-Centric Orientation



Source: Author

3.3.1. CUSTOMER CENTRICITY AND INTEGRATION

This section is an introduction to the concept of customer centricity. Customer-centric orientation is adjusted as a concept 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, but also that customer centricity goes beyond market orientation (Svensson & Gummesson, 2008). Both originate from the same underlying marketing philosophy of Levitt and the theory that information must come from the market while setting up commercial plans (Zolin et al., 2004). On the other hand, customer centricity is about individual customer oversight and interaction with that individual customer. It stresses more the nature of dialogical interaction with the customer, customer-centered processes and the individual customer intelligence (Ramani & Kumar, 2008; Shah et al., 2006), while market orientation places more emphasis on information exchange among functions (Narver & Slater, 1990).

As per Marsh (2010), it is about looking into services that customers really need rather than developing new products and persuading consumers to purchase them. As opposed to customer centricity that 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 behaviors and therefore are less impactful on profitability (Kamakura et al., 2005). The customer-centric organization is often, in theory, in contrast with its opposite - the product centered organization (Galbraith, 2005).

While market orientation urges the need for companies to be responsive to market requirements (Jaworski & Kohli, 1993), customer centricity goes beyond market orientation in that it applies the principles of inter-functional coordination (Narver & Slater, 1990). It also emphasizes the need to develop a customer intimacy as per Antaikainen et al. (Antikainen, Mäkipää, & Ahonen, 2010; Shah et al., 2006) in the process of value co-creation engaging a firm and customers' resources (Prahalad & Ramaswamy, 2004).

Lamberti (2013) states that customer centricity is a very fluid and ambiguous topic. There are descriptive works on customer centricity practices (Wagner & Majchrzak, 2006), papers on contextual factors facilitating the implementation of customer centricity (J. Sheth, Sisodia, & Sharma, 2000), and work on roadmaps towards customer centricity in a firm (Galbraith, 2005).

Criticism about the actual sustainability of a purely customer-centric approach has also emerged. Svensson and Gummersson (2008) suggest that customer centricity may be adopted just in part by some firms and should be balanced by a resource focus. Customer-centricity is a reasonable strategy only in some competitive environments. It hinges on whether competitors have already adopted customer-centric structures, and almost all customer needs are understood and already addressed (J.-Y. Lee, Sridhar, Henderson, & Palmatier, 2015).

Reaching an operational customer-centric business model is complex and time-consuming, and it is often the case that enterprises underachieve the expected change in customer experience (Leather, 2014). Organizational culture, structure, processes, and financial metrics of the firm are issues on the path to customer centricity (Shah et al., 2006).

Customer-centric firms favor having a decentralized organization that provides the possibility to change quickly and learn fast, adapting to dynamic customer needs (Treacy & Wiersema, 1997). Kotler (2003) argues that all functions need to work in synchronicity in all communications, meaning that there is no departmentalization in a customer-centric approach.

Organizational and information integration is one of the operational dimensions of customer-centric orientation for the purpose of this research. 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. Similarly, Tsiotsou (2009) hypothesizes that customer orientation directly influences service performance, whereas inter-functional coordination has the same indirect effects through customer orientation. Galbraith (2005) reports the need for a common cross-functional goal shared across functions in order to implement customer-centered processes. Customer-centric marketing activities are cross-functional processes (O'Leary-Kelly & Flores, 2002).

Having all functional activities integrated and coordinated in delivering top class customer value is one of challenging need, and significant organizational change is required to achieve that. Different disciplines have focused on different organizational activities or components related to integration. Integration is a frequently used term in literature, and there are different constructs of what it means: operations that were not meant to operate together achieving mutual success, even not fused into one entity; units association; communication activity intensity, where meetings and more informational streams between lines of business increase, stimulating teamwork, sharing resources and achievements, composite of interaction and collaboration (Lawrence & Lorsch, 1967).

There is an ongoing need to translate customer centricity into market performance and firms need to clearly define the organizational role of the sales function in that process (Ingram, LaForge, & Leigh, 2002). For instance, Matthyssens and Johnston (2006) raise the need for a redesign of the traditional organizational structure and 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. The coordination and co-use of resources - lead to a better balancing of decision making and responsibilities in a chain. There is a need for additional background on this intersection of integration concept with the customer-centricity concept.

The theory of the firm from Coase (1937) provides the theoretical underpinnings for the firm as a set of integrated units being influenced by the heterogeneity of the firm's actions. According to current research, market-related activities are carried out by several functions such as product management, field sales, and customer service (Möller & Rajala, 1999). The key challenge for customer-oriented units management and for marketing management is in the coordination of the interfaces between these units, between them and R&D and production, and between them and the corresponding organizational units of customers (Möller & Rajala, 1999). Moorman and Rust (1999) view marketing as the function that manages connections between the organization and the customer (i.e. the customer-product, customer-service delivery, and customer-financial accountability).

On the other side, several suggestions have been put forth that the product management functions could potentially be effectively used as a coordination mechanism. The functional boundaries disposal and reorganization that took place after 1990 has resulted in the assignment of more responsibility and power down to the product lines and product managers as a result of adopting a process-based view of arranging tasks and activities (Möller & Rajala, 1999). Hutt and Speh (1984) notice that the literature did not investigate the complexity of interrelationships that exist between marketing and the other business functions, as well as their importance.

Similarly, Gupta et al. (1986) are questioning what level of integration is needed per type of organization. Freeman and Soete (2000) outline that only opportunists require a high level of integration between sales and marketing to take advantage of a market opportunity. Kimberly et al. (1978) state that information processing and the degree of integration required between R&D and marketing needs are greatly reduced as firms move from the prospectors to the reactors category. Lawrence and Lorsch (1967) add to this that the greater the environmental uncertainty, the greater the specialization or differentiation within the organization is, and that brings coordination difficulties. Thus, high environmental uncertainty is likely to necessitate greater information processing and greater integration among organizational subsystems. Although complexity is a function of the number of specialists in the organization, successful innovative companies are likely to have more specialists (Jeffrey Ford & Hage, 1981). Wind (1981) reports integration problems in centralized structures with a hierarchy of authority and a low degree of participation in decision making. A greater the degree of integration will be achieved if there is a low concentration of power and low formalization (rules and procedures in performing one's job), and high employee participation in the new product decisions.

Lamberti (2013) supplied an operational view of its constituting elements of customer-centric construct: (1) generating, integrating and consolidating data into intelligence to understand customer explicit and hidden needs (interactive customer relationship management); (2) a systematic involvement of customers in marketing and new product development decision making (customer integration); (3) strongly coordinated organizational structures to manage the interface all along the touch-points (internal integration); and (4) the presence of a supply-chain coordinated with the firm and able to face the customization required by customers (external integration).

Shah et al. (2006) insist that there is a way to overcome major barriers in the way to customer-centricity, driven by strong (1) organizational realignment, (2) systems and process support, and (3) revised financial metrics and leadership commitment.

Customer-centric orientation is an adjusted concept derived from Shah et al. (2006) and (Lamberti, 2013), 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.

State of the art research for customer centricity focuses on practical frameworks; for instance using customer centricity as a framework to align service delivery with the customer's expectations (Malhotra, 2017), and organizational culture, in particular, and measures for fostering a customer-centric impacted culture throughout the organization (MacGillavry & Sinyan, 2016). It could also pertain to a customer-centric culture relationship to knowledge creation that increases customer satisfaction (Bedarkar, Pandita, Agarwal, & Saini, 2016), leveraging new technologies (for example CRM predictive analytics (Boujena, Coussement, & Bock, 2015) or existing Web APIs (Nikou & Chatzigiannakis, 2015)). As well, it could involve the use of big data and statistical data analysis (Rugel, 2014), and achieving customer centricity through business process management (BPM); for instance to obtain a profound understanding of customers' processes (Trkman, Mertens, Viaene, & Gemmel, 2015) or to measure the maturity of customer-centricity via BPM adaptation (Vojvodic & Hitz, 2018).

3.3.2. CUSTOMER-CENTRIC ORGANIZATIONAL INTEGRATION

This section rationalizes organizational integration (combined from internal integration and organizational realignment), as one of three dimensions of customer-centric orientation. Organizational integration is conceptualized with several elements that would support its further operationalization: measuring the amount of joint work together, awareness of each other's responsibilities and prioritization of customers.

Organizational integration is the extent to which distinct and interdependent organizational components constitute a unified whole. In such definition, if fused with the concept of customer centricity, the term component would refer to customer relationship management oriented organizational units, departments, or partners and include the business processes, people, and technology involved (Leavitt, 1964). Organizational integration is measured by adaptiveness and adjustment of one unit to the demands of others in responsiveness that needs to be processed rapidly and adequately. According to Grant (1996a), integrative efficiency is measured by the effectiveness in receiving and interpreting messages sent by other members, and effectiveness in an appropriate response.

Resource and capability-based theory of the firm from Grant (2011) and Barney (2011) provides the means for the understanding of effective organizational arrangements for customer relationship facing units. According to Cespedes (1995), market-facing and customer-facing activities are spread amongst three units: product management, sales, and customer service.

For Lysonski (1985), what is important to product managers is that they balance inputs and requests from several internal units and from customers as well as they balance technical development aspects of their products with business level product-market decisions (Möller & Rajala, 1999). This gives them additional responsibility and importance. The salesforce is normally a company face in front of the customers and one of the key boundary roles in organizations (Cespedes, 1993). The field sales function in industrial companies is often organized as a standalone department or even a subsidiary at distance due to the geographical spread of operations. Firms in practice have additional units for customer service and maintenance purposes in order to support sales, providing post-sale service, giving customers the necessary support in installation and training. Cespedes (1995) elaborates on the way such companies generate increasingly higher parts of their revenue by providing and monetizing these different types of services to customers, beginning from installation and training, and ending with long-term maintenance contracts (Möller & Rajala, 1999).

Customer and market facing tasks become knowledge-intensive and a natural reaction to handle that intensity is in informal non-hierarchical groups such as project teams, key communicators, and teams within a business process setting (Nonaka & Takeuchi, 1995). Business process-oriented organizational solutions broke apart traditional single unit department (sometimes named marketing unit) across several organizational units. This established nets of the customer and market-facing activities spread across complex matrix organizations, multifunctional teams and account management systems (Achrol, 1991; Cespedes, 1993). A necessary critical element for the efficient management of customer relationships became an integration of such internal, corporation-wide network of marketing and customer related units (Möller & Rajala, 1999).

The challenge of customer relationships is that there are many actors such as account managers, project managers, product managers, and marketing communication managers involved in the relationships. Some of the crucial goals for management are integration, good communication, and coordination of activities between all these actors. The number of these units and their decentralized character puts great pressure on inter-unit coordination and communication. 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). Sales and marketing often have different goals set by senior management, leading to lack of coordination of activities (Colletti & Chonko, 1997).

It is argued that new centers, comprising representatives from all the relevant units, should be formed, with responsibility for inter-functional coordination and the integration of the diversified marketing units. Centers would be managed in such a way that both marketing, product development, and production expertise are present in them all the time. This means extensive use of a different type of project-based teams, even including representatives from customers, partners, and sub-contractors. A plausible explanation can be found from Porter (1998) and the ideas of the value chain, and Davenport and Short (1990)'s business process redesign context (Möller & Rajala, 1999). Adoption of process-based monitoring of tasks and activities showed that department-based line organization is inefficient, while process organizations can provide more efficiency and quick adoptions, but demand lean structures. That should not be a challenge as basic business functions (such as marketing, R&D, and production) actually already can be seen as activity flows (Möller & Rajala, 1999). Primary customer value–creating processes are creating solutions the customer wants, creating customer knowledge, building customer relationships, and shaping customer perception under customer relationship management (Srivastava, Shervani, & Fahey, 1999).

There are rich theories behind customer-organizational integration. Hult (2011) delineates a theory of the boundary-spanning marketing organization, rooted in an organization's capabilities from Day (1994), where the integration of customer value–creating business processes is a major driver of success. Gupta et al. (1986) put forward a theoretical framework for the study of R&D - marketing integration and define internal integration as departments' interdependency in operations or procedures that require co-operation with the aim to have better coordination between functional areas. Based on Archol and Kotler (1999), the theory of network organizations can be integrated with boundary-spanning marketing theory. A network organization can combine weather units or firms and they maximize the productivity of serially dependent functions by creating partnerships among such independent skill-specialized units or firms. The greater the resource dependence leads to the greater level of flows of work, and assistance between them (Ruekert & Walker, 1987). For Anchrol and Kotler (1999) the network of organizations operates without hierarchical control where their lateral connections organically create a shared value system that defines membership responsibilities. Thorelli (1986) argues that even the entire economy may be viewed as a network of organizations.

3.3.3. CUSTOMER-CENTRIC INFORMATION INTEGRATION

This section focuses on information integration (combined from interactive customer relationship management and systems and process support), as one of three dimensions of customer-centric orientation. It would assume the rate of customer data being integrated, consolidated and used for analysis.

The concept customer database centrality, proposed by Syam et al. (2005) was empirically confirmed in the study of Lamberti (2013), where interviewees agreed that customer centricity requires a deep knowledge of customers. Yang et al. (2007) state that various stakeholders would need to have accurate information about the customer at the right time, as well as provided in a systematic manner, from different stages of the data lifecycle. Even the chief customer officer's role is about monitoring all and new key intersection points that impact customer decisions to stay, leave, buy more, and recommend and drive executive appetite for wanting to know about these interruptions in customers' lives within their respective functions (Bliss, 2015). Similarly, Date et al. (1988) argue that coordinating operations amongst interdependent parts of the organization brings customer insights from organization-wide communication if information integration processes are in place.

Moving toward a holistic and accurate system-of-record for customer information organizations has been at work for a long time. The number of customers, number of lines of business, and number of sales and service channels continue to grow, and this growth often proceeds in rather ad-hoc and non-strategic and non-integrated fashion. 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).

Hollander et al. (2013) elaborate that barriers to successful transformation to customer centricity come from obsolete, not consolidated and not adequate systems and processes, a lack of customer data or their poor quality. Strong organizational silos create barriers to share customer data or cooperate across functions and departments. Adding new channels and complex products or policies are leading to an astonishing proliferation of data silos with duplicated and inconsistent data.

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). Customer data hubs focused systems became an enabler of achieving informational customer centricity (Berson & Dubov, 2011). They are requested and funded usually after vast data discrepancies and incompatibilities become visible when data from silos have to be unlocked, revealed and distributed due to the rise of a need to share information across fields, internally and externally. For Building et al. (2005), customer relationship management (CRM) is usually the first functional customer-specialized system implemented and provides pre-built functionalities for activities such as cross-selling, customized marketing communications or segmentation.

While CRM and DW are 'static', where the latter relates to additional analytical copy of data, with a unidirectional synchronization purpose, the 'master data management' concept is establishing control over major (master) data from a single system of record that will also ensure that all changes in data are replicated across all related systems (Silvola et al., 2011). Smith (2008) aligns with this, arguing that master data management includes a number of activities for creating, modifying or deleting a master data class, a master data attribute, or a master data object. It needs to contain enterprise-wide awareness of all such changes, and its purpose is to deliver master data of good quality (complete, accurate, timely, and well structured) for its usage in business processes (Loshin, 2010). Silvola et al. (2011) outline that master data management projects are usually implemented in firms with multiple applications with master data, such as CRM – customer relationship management, PDM – product data management, ERP – enterprise resource planning, and others.

Two major directions architectures of MDM projects exist. It can be more analytical, if built by extracting master data from source systems (for instance from local ERP systems), transforming them, and finally loading them into a single-view-of-truth system or operational, if master data is being circulated from a central system to local systems which use these data to support business processes (Loshin, 2010).

However, modern demands of customer-centricity have an overinflated value that these information technology systems provide. It is not enough to have a functional, operational or analytical system. In the customer-centric model, communication with the customer is complex and demanding. Whenever the customer dictates, one must be available via a number of channels (customer service, email, web, mobile, agents, affiliates, and social media). Customer-facing enterprises need advanced knowledge of their best and largest customers, organized into groups or individually. This will form the basis for managing customer lifetime value, increase the effectiveness of marketing campaigns, improve customer service, and thus reduce attrition rates.

Advanced customer-centric information management enables an enterprise to recognize a customer at any 'point of entry' into the enterprise and to provide personalized treatment. This improves retention as the cause of many of the factors of turnover rate is the lack of accurate business intelligence about the customer. Businesses can start managing the life cycle of customers beyond their acquisition and analyzing, monitoring and leveraging customer relationships with other entities or potential customers. It gives them access to having just-in-time, accurate, and complete data to improve customer service and create near-real-time cross-sell and up-sell opportunities across various online channels. This can reduce the number of marketing mailings and target the right customers with the right offers (Berson & Dubov, 2011). Data analytics on how to provision accurate customer pricing and risk data, potentially on the fly, in a price sensitive, competitive landscape, impacts commercial success.

Customer centricity and integration of customer information for advanced analytics and data usage cannot be achieved without modernizing the existing line of business systems. The reason for information issues lies in the fact that the greatest challenge to success is not so much technological as organizational. Shah et al. (2006) elaborate on this with a summary of previous experience with customer relationship management projects, a point of massive investments in what was considered customer focus, and equally extensive area of failures and disappointments. Likewise, Fader (2012) notes that companies who put Customer Relationship Management (CRM) systems into place eventually deem their efforts to be failures, as their goal is just to implement the system across the company and presumably, smart decisions would follow automatically. Almost inevitably, it devolves from a potentially groundbreaking strategic tool into a very expensive, very burdensome exercise in systems engineering. After gathering tons of data about their customers, having made no organizational culture, structure, leadership or process related transformational changes, companies eventually forget what CRM was supposed to be in the first place (Marsh, 2010). Master data management organizational implementation follows many issues that emerge along the way. Even from the technical perspective to be considered as a successful implementation, an MDM project often is not able to fulfill the business objectives and is considered a failure (Vilminko-Heikkinen & Pekkola, 2013).

3.3.4. CUSTOMER CENTRIC STRATEGIC DIRECTION

Besides customer-centric information, integration is described in the previous chapter. It is also highlighted that 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. This section highlights organizational integration (includes revised financial metrics and leadership commitment), as one of three dimensions of customer-centric orientation. In the previous chapter, it was justified why customer centricity involves a decision on strategically changing a firm's direction. This section argues that such direction would include appropriate customer-centric changes in organizational culture, leadership, and measurement related practices. Besides the change in organizational structure and processes, as stated by (Shah et al., 2006), organizational culture, leadership and financial metrics of the firm are major elements the path to customer centricity.

Fader (2012) notes that the significance of organizational culture in a customer-centric company assumes that individuals strive to provide to every customer the quickest and most complete answer to any of his questions. Even if the ideal adaptation of the organizational structure is in place to support this smooth flow of answers, the outcome for customers would still be insufficient if the development of a proper culture did not complement structure change (Lamberti, 2013). Corporate culture is important for carrying out programs and projects aimed at the corporate or technological development of the organization. Corporate culture serves as an indicator for determining the values, the attitudes and beliefs and the roles of people (Ravasi & Schultz, 2006). Organizational culture is described by Robbins and Coulter (2005). stating that organizational culture is shared values, beliefs, or perceptions that employees hold within their department or the whole organization. As such it can influence the attitudes and behavior of people, even so far that it can improve performance (Denison & Mishra, 1995). Deal and Kenney (1982) prove that a strong culture is a system that strictly impacts how people behave. Management has a considerable amount of values in the valid analysis of the cultural impact on employee-related variables, such as job satisfaction (Lund, 2003), organizational commitment and performance (Tsai, 2011). Isaksen (2007) states that making organizational transformation happen is best approached through a systemic or ecological approach that clarifies what leaders can do to transform culture and climate. An organization (or an area of an organization) that wants to be successful in its lean journey must first measure its organization culture and then promote a cultural profile aligned with the results (Paro & Gerolamo, 2017).

In essence, leadership commitment is critical for both initiating as well as sustaining all initiatives for customer centricity. This includes those initiatives related to organizational culture, structure, systems and process support, and revised financial metrics (Shah et al., 2006). The challenge is ensuring that customer centricity becomes a key priority for management. The location of authority in the organization structure, as much as the structure itself, are critical success factors in implementing a customer-centric strategy. According to Galbraith (2005) in product centric organizations, the managers of the customer relationship are on the side of the seller, in that they are interested in pushing more features, better products, or more products. In the customer-centric organization, these people are more 'on the side' of the customer, as their interest is in providing the best possible customized outcome for their particular customer. Marsh (2010) claims that the effective placement of people who are in charge of the customer-centric initiative high on the hierarchical level causes all parties involved in the organization to have the same complexity of understanding of the business model, at the very least. While moving to a higher level or internal integration of an organizational structure change, interaction between units can be increased in two ways - by adding more of resource dependence, as exchange and interaction take place more frequently among people in departments belonging to similar resource domains, and by clear strategy given by top management that dictates inter-functional interaction (Ruekert & Walker, 1987). Many leaders do not have the courage to commit to the required transformation of developing and implementing organizational capabilities that enable a customer-centric business model. Besides, personal incentive is often in conflict with customer-centric capability. Many organizations are unable to evolve to the cultural changes required if there is no authority responsible for creating customer strategy at the highest level of the organization in order to maximize the drivers of customer value management such as retention, customer development or cross-sell. Customers indeed are a finite resource and the source of all revenue and profit, today and tomorrow and therefore the most valuable asset of any organization. And in most cases, there is no one with the responsibility of managing that asset (Leather, 2014). Around the world, the customer leadership executive role has been embraced. The role of the chief customer officer (CCO) is created to drive a unified focus on customer experiences, to fix what annoys customers and to urge silos to take action. The role becomes architect and facilitator, uniting leaders to make decisions of investing in the most impactful priorities that improve customers' lives and leads to business growth (Bliss, 2015).

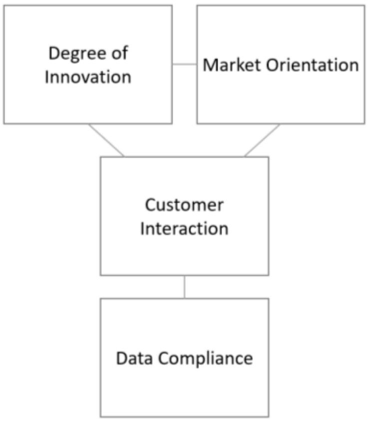
Reinartz and Kumar (2003) argue that customer management-oriented organizations recognize the dynamic and importance of the evolving nature of the customer-firm relationship over time. The basis of this recognition is an understanding of metrics, such as customer lifetime duration, customer lifetime profit and the drivers behind them. Financial customer metrics are not only important in motivating individual employees to be more customer-centric but in helping measure the financial implications of decisions made, as a path to customer centricity often involve a substantial investment by the firm to facilitate the transformation. Hollander et al. (2013) argue that the balance of customer-centric principles with financial considerations is critical. Shah et al. (2006) further suggest that firms should include at least two or three of the most important customer metrics among the key performance indicators that are reported regularly to the top management and the board.

An equally important task is synchronizing the incentives and rewards system with the customer-centric paradigm. This may be as simple as ensuring that employee appraisal and salary revisions are based on clearly defined customer contact metrics or customer outcomes (G. Day, 2000). Even the human resources function can redefine itself by managing with the philosophy that customer satisfaction and loyalty are the cause and result of employee satisfaction. This concept can be institutionalized by evaluating employees based on measurable improvements in customer satisfaction and loyalty. The key competence of the chief customer officer in such a role is uniting leaders in establishing customer asset metrics and customer growth behaviors that the management will stand behind as a united leadership team (Bliss, 2015). Gupta and Zeithaml (2006) divided metrics into observable measures (customer acquisition, retention, and lifetime value) and unobservable constructs that include customer perceptions (ie. service quality), attitudes (ie. customer satisfaction) or behavioral intentions (ie. an intention to purchase).

3.4. DATA COMPLIANCE INNOVATION

This part of the theoretical background conceptualizes the Data Compliance Innovation (DCI) construct. The first part covers the degree of innovation and market orientation. Data compliance and innovation in customer interaction orientation are covered in the second part (Figure 7).

Figure 7: Data Compliance Innovation - Theoretical integration of concepts



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3.4.1. DEGREE OF INNOVATION AND MARKET ORIENTATION

This section focuses on the innovation part of the concept of data compliance based on the integration of innovation and market orientation theories.

Slater and Narver (1995) define the profitable creation and maintenance of superior customer value as market orientation highest priority. Similarly, Menon and Varadarajan (1992) elaborated on market orientation related to the organizational culture and innovativeness. Nevertheless, innovation is a wider concept that addresses the implementation of new ideas or processes (Thompson, 1965), and not necessarily entering new markets and serving customers. Likewise, Jaworski and Kohli (1993) argue that if the basis of market orientation is a code of doing something new or different in response to market conditions, it may be viewed as a form of innovative behavior.

There is a large volume of published studies describing the role of creativity and innovation as key components of competitive advantage. Im and Workman (2004) confirm this. Firms capable of using their resources most effectively will benefit from greater profits in the current competitive environment (Porter, 1998). Real resource utilization is based on the leadership creating unique solutions to existing business problems, utilizing innovation and creativity (Naletelich, 2015). Likewise, Ritter et al. (2002) illustrate that effective interactions with suppliers, customers, and other organizations in the area of network competence lead to competitive strength and performance.

However, it is not adequate to claim focus on innovation without understanding its range. Innovations are assessed across several dimensions according to Gatignon et al. (2002). They list them from the core to peripheral innovations; incremental to radical innovation types; architectural to disruptive innovations. Kiem and Maubourgne (1997) report that there is a need for compelling innovations, as opposed to mere marginal enhancements in cost efficiency or quality that lead to the 'competition trap' and just the subsequent addition of similar strategies. Boer and Gertsen (2003) support the idea that discipline in innovation builds concept named continuous innovation, which would consist of continuous improvement, learning, and innovation. Innovation theory is an established area of research, and continuous improvement and learning are emerging as its next, more advanced form. A collection of studies on organizational learning is not empirical enough and not validated rigorously, while continuous improvement provides the basis for good empirical proofs.

Value improvements for customers are the objective of strategic innovation (W. Kim & Mauborgne, 1997). Schlegelmilch (2003) defines it as the customer getting placed higher than the competition on the strategic thinking scale. Actually, the idea of mixture of innovation and strategy evolved under the name of strategic innovation (Krinsky & Jenkins, 1997), as a symbiotic union of two bodies of knowledge, strategy and strategic planning, one with heritage on the corporate and business unit levels, and the other one with highest achievements made on the product level (Varadarajan & Jayachandran, 1999). Kim and Maubourgne (1997) argue that strategic innovation actively participates in shaping markets and external trends, rather than just reactively adapting to external trends.

A considerable amount of literature has been published on the factors that influence the process to become more innovative. The mechanism for achieving a continuous innovation goal is in the ability to appropriately configure processes, procedures, people, technologies and organizational setup (Boer & Gertsen, 2003). Zaltman et al. (1973) propose initiation and implementation as two diverse phases of the innovation process, having openness to innovation as the strongest fragment in the former. Kimberly and Evanisko (1981) recommend focusing on innovation (implementation of new ideas, products, or processes) rather than learning (development of knowledge and insights) as a way to succeed in a model of market orientation.

Alternatively, Want and Chung (2013) state that market and learning oriented cultures both encourage openness to new ideas and should be kept. Literature supports that firms with a customer focus tend to be more proactive in meeting customer needs and that, when measured, customer orientation has a positive impact on innovation. There are also works that show evidence that market orientation only moderately positively relates to the innovative orientation of a firm (Grinstein, 2008).

Some other organizational factors are as well present in rationalizing how to become more innovative. Han et al. (1998) recorded that inter-functional coordination is related to the development of new products and services, although it is not positively related to organizational innovativeness. In order to generate more creative thinking and innovation, teams from different functional areas are being established (S. Jackson et al., 1995). Kim and Maubourgne (1997) argue that a culture of continuous curiosity and questioning of an overall view of the business, involving ideas and beliefs about the customers, and technology is a precondition to strategic innovation.

Similarly, Hurley and Hult (1998) claim that market and learning oriented cultures both encourage openness to new ideas. Additionally, Burns and Stalker (1994) argued that decentralized organizational design, with fluid and indistinct job responsibilities, triggers employees to start to cooperate and share information. High structural uncertainty leads to informality between organizational units and the effective dispersion of knowledge (Anil Gupta & Govindarajan, 1991).

Mintzberg (2003) recommends distributing experts in functional units as a second priority, assembling them in cross-functional teams for specific tasks as being their real priority. Wang and Chung (2013) recorded that inter-functional coordination enables a corporate culture that is more receptive to innovation – and to grow innovation, new products, and services. Anil Gupta and Govindarajan (1991) suggest a broad set of mechanisms such as cross-unit committees, integrator roles, shared databases, and matrix structures as a means to attract and enhance information sharing and discussion. Bahrami (1992) and Miles and Snow (1992) summarized the role of multi-functional groups in the formation of new processes.

There are already authors that suggest measures for the degree of innovation. Leadership towards innovation starts with the measurement of the innovation capacity in the enterprise (Cordero, 1990). Sarin and McDermott (2003) define the level of innovation as the degree of newness of the product under development. Doroodian et al. (2014) proposed the following dimensions of innovation capacity: knowledge and technology management capability, idea management capability, project development capability, and commercialization capability.

3.4.2. DATA COMPLIANCE AND INNOVATION IN CUSTOMER INTERACTION ORIENTATION

The previous sections show that the concept of customer interaction can be integrated with market orientation focused innovation. This section applies that integration in a setup of data compliance with GDPR as an example and customer engagement and interaction orientation concepts.

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 behaviors in order to drive trust, loyalty and even new services.

Customers of every data processing firm will expect compliance with GDPR and therefore simply fulfilling this is not in any way gaining a competitive advantage. On one side, to gain a competitive advantage the response must be used to engage with customers in a new way and to innovate on that way. The changes are an opportunity for businesses to gain greater insight into their customers' needs (Sawhney et al., 2005). An end-to-end approach to the asset of customers' data is growing as practice for effective GDPR response. Different functional areas are managing and continually enriching and optimizing a common data set of customers' data. A GDPR project is a perfect catalyst or first step towards establishing a common data model for customer data. This needs to be followed with an extension into enterprise data as a service fueling customer-facing functions operations and competitive advantage (Mantelero, 2016).

Economic, political and social activities are moving online, changing the interaction between individuals, businesses, and government, and giving wide scope for innovation. Contributions to commercial success come from the analytics on how to provide the customer with accurate pricing and risk data, ad hoc, in a price sensitive, competitive landscape, if based on accurate and real-time insights (Mantelero, 2014).

Data are becoming new assets and firms need to add this to the focus they have been so far giving to property, plants, equipment, inventory, cash, and intellectual property. Enterprises need to adapt and define their ideal position and role in the data economy (Opher, 2016). Flows of data have created new infrastructure and new businesses and initiatives. Firms must evaluate their engagement in them (The Economist Group Limited, 2017).

The decrease in the cost of storing data has made it possible to capture, save, and analyze a much larger amount of information about individuals, consumers, and customers as listed by Acquisti (2010). Rich datasets of customers expand a firm's marketing better by targeting narrower specific markets, bringing down advertising costs while improving consumer loyalty and revenue. Ability to predict aggregate trends and change in preferences comes with a proper analysis of these customer data. Profit-enhancing and legal price discrimination is an economic opportunity in the existing non-regulated environment (Varian, 1985).

Anil Gupta and Govandarajan (1991) showed that extensive use of information technology positively impacts rapid awareness of as well as response to competitive and market change, more effective sharing of information, and a reduction in the lag between decision and action. Innovation and improvement of services and products are facilitated by observing customer activity so precisely. Organizations also can monetize these data as behavioral data generated on the platform (Tallon, 2013). Customers might receive immediate monetary compensation for revealing personal data (e.g., discounts), receive personalization and customization or benefit from data-driven improved services. With this, consumers are getting innovative and new products that otherwise would never exist as they are too risky to develop without consumers' data. Prices might, sometimes, be reduced as an effect of more targeted (and less wasteful) advertising and marketing.

A powerful economic engine raised in recent years is called 'the data network effect' - using data to attract more users, who then generate more data, which helps to improve services, which attracts more users (The Economist, 2017). Important economic characteristics of digital data are economies of scope and data trade and data-driven mergers to drive lower costs in data collection and analysis (Rosen, 1983). The algorithms learned from one dataset may in some cases be transposed to other datasets. This describes why data-driven firms are so 'data hungry' to collect all the data they can get (Duch-Brown, 2017). Palfrey and Gasser (2012) claim that extreme interoperability creates this potential as a digital format of information can be stored, replicated and transmitted much faster and at a much lower energy cost.

Firms might utilize rich datasets of consumers to enhance marketing and target more specific group of customers, decrease advertising costs, increase revenue and consumer loyalty. Insights generated in large amounts of data predict aggregate trends and more granular individuals preferences, equip profit-enhancing price discrimination (Varian, 1985), re-design process, service or product according to the observed behavior, selling data to marketers, advertisers, and data aggregators interested in the behavioral or user-disclosed data.

Determining which datasets a company should monetize or acquire is on its own complex decision. Companies should consider their strategic objectives, data access, and control the ability to consistently collect data (Opher, 2016). In each case, 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, 2013). Trade-offs can be approached gradually, as advancements in information technology technical measures make it possible for data to be easily split into packages and displayed in bits (Duch-Brown, 2017).

The way to take advantage of the personal data concerns and regulators activity is to utilize granular measures of these data in order to add value for customers. Sustained personal engagement and ongoing success in addressing exact customer desire will generate loyalty. Alvares-Bermejo et al. (2016) and Myles (2015) claim that making data, permissions, and control accessible 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. Granular measures of data and management of customer personal data with extreme caution lead to innovation, services, and ideas on how to make the customer happier. Organizations can improve the customer experience by triggering more relevance from and a complete view of customer data, having monitored attributes on how a customer wants to be engaged in actions (Bolognini & Bistolfi, 2017; Braun & Garriga, 2018; Kasabov & Warlow, 2010).

With adding more value to the data returned and displayed within data compliance requirements, 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 alongside compliance-driven activities (Kumar et al., 2010). Through customer data, there are opportunities to deliver improved customer satisfaction and perform smarter working. 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. On top of that, working collaboratively together with the customer can give a richer extension on these data, and it also helps to build trust and confidence (Burgoon et al., 2015).

Brodie et al. (2011) note that within modern interactive environments, customer engagement represents a strategic imperative for generating sales growth, superior competitive advantage, and profitability. Customer engagement goes beyond sales and considers a firm's longer-term goals and motivational drivers beyond purchase (van Doorn et al., 2010). Such engagement and interaction give the opportunity that each buyer journey should be handled uniquely, with analysis and implementation of the multiple data collection sources to properly and successfully segment customers based on browsing behavior (Kunz et al., 2017). Modern information technology enables customer-centric processes and cross-functional integration (Shah et al., 2006).

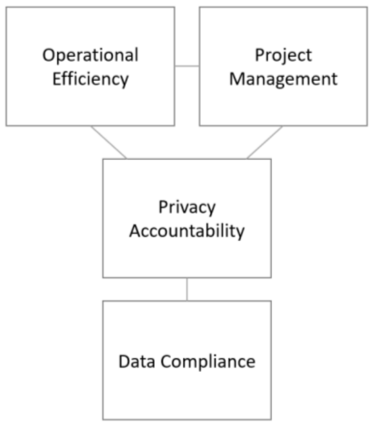
Systematically classifying customer processes provides a collection of customer data that show the most popular process routes, from the starting point of acting to the end-point of need satisfaction. Customers expect an analysis of data that goes beyond the standard profile data – birthday, gender, name. Gregory and Bentall (2012) argue that it is vital to collect the most optimized and beneficial data through web analytics, mobile applications and offline, and to collect more data than primarily planned. This can be done through the addition of third-party apps such as clicks, downloads, and opens. 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). Ramani and Kumar (2008) suggest that the technology 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.

Data need to cross all aspects of the customer relationship and link data silos, while the trusted enterprise view of customer data obviously is a necessary prerequisite (Edge, 2014). In the customer-centric model, communication with the customer is complex and challenging, where the data lifecycle needs to be known alongside undoubted trust in the data. Important market and customer-related decisions are based upon them, and regulators will want to know such lifecycles as well.

3.5. PRIVACY PROJECT EFFICIENCY

This part of theoretical background conceptualizes the Privacy Project Efficiency (PPE) construct and covers the concept of operational efficiency and project management in the first part and data compliance privacy accountability in the second part (Figure 8).

Figure 8: Privacy Project Efficiency - Theoretical integration of concepts



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3.5.1. CONCEPT OF OPERATIONAL EFFICIENCY AND PROJECT MANAGEMENT

This section integrates the concept of operational efficiency with the concept of project management. Establishment of accountability for customer privacy protection is one of the governance-driven projects that requires efficiency in data compliance. Accountability is distributed across operational data stakeholders in all functions, including line-of-business stakeholders.

Operational efficiency refers to leading and controlling, measuring and improving the processes with eventual process performance gains (Santa et al., 2011). It is about the establishment of processes that work optimally based on core capabilities within the organizations (M. Porter, 1998). The firm will outperform competitors if core processes have eliminated waste, reduced costs, in addition to adopting appropriate technology innovation (Porter, 1996).

The five performance dimensions of operational efficiency are cost, quality, flexibility, speed and reliability (Hill, 2005). Improving cost performance comes from the elimination of waste inefficiencies attained in processes such as purchasing, production, and staff performance. Operational processes get improved by the accumulation of patterns of routines and practices (March, Simon, & Guetzkow, 1993). Enhancement on quality of services that satisfy customers rather than simply conforming to specifications without any clear continuous improvement is an example of operational effectiveness. Improving on speed shortens the time between the service request and delivery of the service and that would be operational efficiency (Hill, 2005). In modern times, the objective of being flexible and the ability to quickly adjust to changes in response to customers' needs raises the importance of operational efficiency (Slack, Brandon-Jones, & Johnston, 2013). Business process reengineering is one of the operational efficiency movements that has largely been replaced by enterprise information systems initiatives in the last decades (Davenport & Short, 1990).

There is still a discussion on what exactly is the definition of project success without any agreed approach in measuring it (Todorović, Petrović, Mihić, Obradović, & Bushuyev, 2015). Some authors consider matching the aspirations of the project stakeholders and opposing requirements for project quality, scope, time, and the cost is considered as project success (Aga et al., 2016). Some scholars (Z. Yang, Ding, Zhou, Cai, & Zhao, 2010) use strategy of unification of measures of project success, while others (Diallo & Thuillier, 2005) use disaggregated measures. Project efficiency is predominantly used to measure project success, meaning fulfillment on schedule, with agreed costs and quality (Berssaneti & Carvalho, 2015). "Iron triangle" is a famous term used for the dimensions of speed, cost, and quality in projects (Toor & Ogunlana, 2010). The project was believed to be successful when the final total costs fit with the intended budget and the predicted schedule was met (Atkinson, 1999).

In some recorded studies - the basis for the measure is projected efficiency (how costly the project is compared to the results), and project effectiveness (how much are the objectives achieved), impact and positive and negative changes produced by the project, and finally sustainability and how much benefits of the project are likely to continue without further funding (Ika, 2015). Due to the importance of strategic capital projects, success factors are in such cases sometimes extended by factors such as quality of planning, cross-functional integration, stakeholders' satisfaction, impact on the customer, business success, project team satisfaction, opportunities for future growth, etc. as a result of project (Frinsdorf, Zuo, & Xia, 2014). 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, while fulfilling the technical goals of the project.

Finally, project efficiency is the most often used measure of project performance (Serrador & Rodney Turner, 2014), with many researchers considering it as one of the key metrics of project success (Srivannaboon & Milosevic, 2006). Efficiency is described whilst distinguishing it from effectiveness (Sundqvist, Backlund, & Chronéer, 2014), where the former one refers to meeting all internal requirements for cost, margins, asset utilization and the latter one relating to satisfying the project client expectations. When resources are used to maximize returns within the planned schedule and budgetary constraints, the project is considered efficient (Frinsdorf et al., 2014).

How to advance project management practices in order to make a project more successful - has been the focus of both practitioners and scholars for a long time (Kieser & Nicolai, 2005). Time-based project performance, as vital to the competitiveness of an organization (Droge, Jayaram, & Vickery, 2004), became commonly prioritized compared to other factors (Kog, Chua, Loh, & Jaselskis, 1999). Speed is especially significant in the modern competitive global environment as time-related project failure is frequently connected with the unrecoverable loss of revenue (Scott-Young & Samson, 2009). Regardless of so much focus on time dimension, too often projects experience costly delays in completion ((Belassi & Tukel, 1996) and (Leung, Ng, & Cheung, 2002)). Project escalations are in most cases related to the risk of not fulfilling the project on time (Iyer & Jha, 2006).

Project work is characterized by a multi-disciplinary nature (Hobday, 1998). Project teams are frequently diverse, as they assemble specialists from different functional areas in order to perform complex tasks (S. Cohen & Bailey, 1997).

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). Measurement is one of the dimensions that impact the success of data governance stewardship in a project, as they are ongoingly measured. For example, for reducing the data defects over the course of the year by the measured percentage (Dyche, 2015). Important project exposure gives them the opportunity to improve 'how they stand' on metrics.

3.5.2. DATA COMPLIANCE PRIVACY ACCOUNTABILITY

Establishment of accountability for customer privacy protection requires efficiency and speed where accountability needs to distributed across operational data stakeholders in all functions, including line-of-business stakeholders. This chapter is integrating accountability from the concept of control with the GDPR accountability principle. This mandates organizations to implement appropriate technical and organizational measures to be able to demonstrate their compliance with personal data protection. At the heart of such implementation was a governance program of reconciliation of sensitive data by identifying any gaps or overlaps in their lifecycle, missing necessary responsibilities assigned to line-of-business stakeholders or other operational data stakeholders. Data protection is narrowed to privacy protection. This is one of the major governance related projects conducted by every company that aims to comply with the regulation. In bigger enterprises, it is led by a data governance stewardship team.

The term "accountability" is disposed to a variety of different meanings within and across disciplines. In everyday usage, responsibility represents an obligation to perform an activity or to ensure that it gets done, while accountability relates to willingness to be answerable for the same. Being held accountable infers that the individuals are rewarded when good things happen (Breaux & Alspaugh, 2011).

Accountability is related to the concept of control. Control systems are designed to hold individuals or groups accountable for their actions or for the results they produce. Accountability-oriented control systems exist at the managerial levels of most organizations. In these systems, the individuals are normally told prior to the performance period what is expected of them

(Charlesworth & Pearson, 2013). Armenakis (1999) validates that control has been a core function of management for a long time. A study by Fayol (1949) lists control as one of four functions of management besides planning, organizing and coordinating.

Research on control and accountability, similar to the research on risk management, is generally seen as being distorted within the domain of management control systems literature (Otley & Berry, 1980). Both simple operating procedures or complex processes can undergo different forms of controls, some of them even administrative and interpersonal controls (Bruns & Waterhouse, 1975). Control systems need to be designed to lead to desired behaviors in different circumstances as people are themselves separate self-controlling systems. For instance, auditors use the expression 'internal control' for the sets of mechanisms designed to prevent or detect errors and irregularities (Benston & Bush, 2008).

Accountability has been used for a number of years in computer science to refer to a requirement that has to be met by reporting and auditing mechanisms (Cederquist, 2005), now giving priority to PII privacy protection. Personally identifiable information (PII) is information that can be linked to an identifiable individual, either directly, for example, a phone number or social security number linked to a name, or indirectly, by triangulation of various types of data held by the data controller. Charlesworth and Pearson (2013) conclude that then for organizations, privacy, involves the application of laws, policies, standards, and processes via which PII is managed.

Regulation and law-driven accountability related to privacy protection mean placing a legal responsibility upon an organization that uses PII to ensure compliance of employees and contracted partners to whom it supplies the PII. Organizations extend such accountability with responsibility for the protection and appropriate use of PII beyond mere legal requirements and hold employees accountable for any misuse of that information (Charlesworth & Pearson, 2013). There should be a universal approach to data accountability, fitting all data aspects and needs of an organization (Weber et al., 2009).

Governance is linked with accountability; it is in its core definition. Data comes with responsibility. Seeing data comes with responsibility for its usage. Updating data brings responsibility with correct data entry. Working with an explanation of data (metadata) comes with the responsibility of ensuring it is consistent with the standards. The above-mentioned levels of accountability are mainly informal, inefficient, and ineffective (Seiner, 2014). The framework, workflow, and process start to reiterate and data governance needs fewer efforts to continue. Additionally, workflow and process capabilities extend the scope of governance to more data and to more people. In an ideal environment, all users adopt a stewardship-minded approach, and process data primarily fulfilling their direct business needs and additionally contributing to the overall requirements for accountability and consistency within the organization (Leenheer et al., 2010).

Breaux and Alspaugh (2011) note that accountability for the protection of privacy of PII in data governance refers to the management of the availability, usability, integrity, and security of such data used, stored or processed within an organization (Charlesworth & Pearson, 2013). 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). Weitzner (2006) claims that accountability based on a governance policy protection has evolved as a concept, from hiding information to ensuring that uses occur (only appropriate ones).

Apart from the demand for holistic reach management of the data about customers, there are new regulations that contain increased requirements related to data privacy, quality, audit-ability, and appropriateness of these data. Regulations like GDPR show that effective management of the data about individuals and customers in firms is not anymore just an internal business and companies are to be fined massive sums for non-compliance. The GDPR regulation requires organizations to prove that they know the location of customers' personal data, and investigate and audit what kind of data is being stored and used. King and Forder (2016a) add that this access is a prerequisite for building an inventory of personal data to evaluate privacy risk exposure and enforce privacy rules across.

The concepts of privacy by design and privacy by default underpin the accountability principle and are at the heart of the shift in mindset that GDPR aims to achieve. It is seen as a recommended structured approach to the design and documenting sensitive data processing operations, anticipated already during the activity of the planning and design phase of operations (Charlesworth & Pearson, 2013). The Centre for Information Policy Leadership (2009) explains accountability as a demonstrable acknowledgment of responsibility for having in place appropriate policies and procedures. In the GDPR regulation proposal (2012), it is noted in "principle of accountability" as demonstrating compliance with the way of adoption of internal policies and mechanisms for ensuring such compliance. In the official regulation document from the EU Commision (2016) the General Data Protection Regulation (GDPR) has the accountability principle in Article 24, which requires that organizations implement appropriate technical and organizational measures to be able to demonstrate their compliance with the regulation. Policy enforcement is a governance term for a technical measure for developing accountability attached to data, and that follows and 'travels' with that data (Pearson & Casassa-Mont, 2011). GDPR technical measures in Article 24 refer to the implementation of appropriate data protection policies. 'Privacy notice' or policy transfer in another entity becomes increasingly important as personal data processing takes place in an increasingly complex technological environment, as even relatively simple transactions cross several data controllers and data processors (Charlesworth & Pearson, 2013).

Boards should ensure that the privacy compliance frameworks that are put in place are capable of ensuring GDPR compliance and that they contain mechanisms for providing regular assurance on the state of compliance across the organization. This governance element must ensure the appropriate 'resource commitment'. A set of process maps could define and document the essential data protection processes that convert the policy into practice. Each specific process should be sufficiently documented so that anyone who has identified responsibilities within the process is clear about what has to be done, by whom, and by when, in a way that will deliver consistent outcomes (Team, 2017).

A number of authors have covered the process of governance reconciliation accountability across the enterprise. Kaniz Fatema et al. (2017) describe that in a 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 and unlinkability, 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).

There are two phases completing the cycle of assigning explanations to data. In the reconciliation phase, data explanations are modeled from existing data, are extracted, refined, articulated and consolidated with assigning them facts, blocking any further misleading explanations of such data (Debruyne & Meersman, 2011). Governance-capture of customers' personal data starts discovering and defining these data, then distributing this understanding across the whole enterprise, including documented privacy rules, blocking any unauthorized access further. To achieve this, accountability must be established in a governance model by linking business terms to physical data sources and establish data lineage from the point of creation to the point of consumption in order to prove the mandatory level of control (Bolognini & Bistolfi, 2017; Hert, Papakonstantinou, Wright, & Gutwirth, 2013).

Governance programs reconcile such data lifecycles by identifying any gaps or overlaps by matching the complete list of necessary responsibilities with those assigned to line-of-business stakeholders or other operational data stakeholders and then assigns missed responsibilities with acceptance process in place. These two lists alongside each other support business users to comprehend their governance role. Stewardship management can address disagreements in the understanding of roles and responsibilities, challenges from ongoing changes in organizational structure, and changes in data ownership. Firms are also reviewing their existing policies, procedures, and practices to ensure compliance requiring intensive data governance stewards - operational data stakeholders communication.

Reduction of the cost of storing information enables the capture, saving, and analysis of high volumes of data about individuals. Details of each customer transaction and activity are recorded and this has been happening without a person's consent or even knowledge. The user does not know how these data will be used and by whom - and does not even ask, as compensated with the immediate benefit of the zero-price service (Capobianco, 2016). Models that prevail on the internet are based on 'free' services provided to individuals in exchange for their personal data. Organizations holding large amounts of data do not enable their customers to control it; they would rather keep this under their control as a competitive advantage (Spiekermann & Korunovska, 2017). The European Union General Data Protection Regulation (GDPR) regulates the processing and use of personal data in the EU. It is a first step in developing a data-friendly environment where privacy preferences are protected, economic interests balanced and innovation motivated (Mantelero, 2014). As such, GDPR is further complemented, developed and continuously updated (González Fuster & Gutwirth, 2013).

3.6. DATA ECONOMY, ECONOMICS, REGULATIONS, AND GOVERNANCE

This part of the theoretical background covers state-of-the-art concerns in the field of data economy, regulations and governance that contribute to the relevance of this research at the present time. It focuses on data economy challenges and governance**,** data regulations, ownership and control economics, the relationship between data regulations, portability, APIs, and open data and EU GDPR.

3.6.1. DATA ECONOMY CHALLENGES AND GOVERNANCE

This section has the aim to describe the complexity of existing economic and regulatory environments that impact and drive data compliance decisions as well as provide new elements of influence on traditional intra-organizational practices, including governance.

Common types of data being sold nowadays include geospatial data, device generated data, business intelligence, advertising, demographics, personal information, research and market data. Data marketplaces have proliferated even more with the growth of big data, as the amount of data collected by governments, businesses, websites, and services has increased and all that data has become increasingly recognized as an asset (Duch-Brown, 2017). Data platforms or data-driven market innovators use their data collection and analytics to facilitate matching users on different sides of the market. An example of this is through buyers and sellers, while not producing any goods or content, where all this intermediation is driven by data (Caillaud, 2003).

A document from the European Political Strategy Center (2017) describes that, due to the rise in data availability and new data-driven insights, more and more data is being exchanged within and among companies. This has spawned a new data economy built upon using data to generate value. Increasing customer expectations and technological advancements transform companies into assembly lines of complete solutions with digital ecosystems of partners. In this way, they raise performance, offering more user-centric products and services, and foster innovation, often leaving decades-old competitors behind. Production strategies shift and collaboration across organizations and ecosystems create a more open flow of information and ideas. The existing and future marketplaces have started to contain an increasing amount of data monetization organizations which core business models rely on these capabilities to present some sort of data, aggregate them, produce them, provide insights or provide data platforms. Companies need to reinvent themselves by defining their desired role in the data economy through an evaluation of their engagement in these ecosystems (Opher, 2016).

Non-sensitive data might afterward reveal sensitive information if linked with new datasets and thus identify an individual. Data values that were valid in the past may not be valid now due to data degradation or even errors. Data may be gathered from sources previously thought of as allowed, and it is often collected without explicit knowledge of that fact.

Varian (1996) notes that the secondary usage of personal data raises particular economic concerns. A consumer may rationally agree to share personal information to receive a net benefit from that transaction, having minimal clarity on how the firm will later use that data. The firm may sell the consumer data to third parties at a profit, without sharing that profit with the consumer. The consumer may even have negative consequences here when the third party exploits this data, for instance for price discrimination (Swire & Litan, 1998). Online companies often propose their products as for 'free', when in fact these involve multiple non-pecuniary costs in the form of providing personal data. According to Friedman's work (2008) on behavioral economics, describing a product as 'free' is deceptive and may affect the consumer's rational decision-making process, making them pay more for the product than they would not do if they were fully informed. The user is given the immediate benefit of the zero-price service but is unaware of the short or long-term costs in divulging information, as they do not know how the data will be used and by whom (Capobianco, 2016).

Data platforms behave like all profit-maximizing firms and use the data to benefit their own position. They are suspected to tweak the matching mechanism in their own favor in order to boost their profits, for instance through price and quality discrimination in their matching algorithms (Duch-Brown, 2017).

Some notable recent works are about user-privacy dimension and the choice between delivering what experience users expect, and protecting user privacy (Pekala, 2017) or individuals becoming active players in the emerging data economy (Crabtree et al., 2016). Others address data certification schemes for open and commercial datasets (Liow & Lee, 2016), privacy-preserving query logs that may be monetized (Bondia-Barcelo, Castella-Roca, & Viejo, 2016), privacy policies understanding by non-technical users (Kununka S., 2017), and the relationship between privacy policies and users' reactions (Gerlach, Widjaja, & Buxmann, 2015).

All consumer surplus is taken away by the firms in secondary usage unless privacy protection is enforced through regulation (Acquisti, 2010). In the document from OECD, the Organisation for Economic Co-operation and Development (2014), it is argued that traditional models of ownership often do not recognize that value is typically derived from the combination and use of data rather than from individual data points. Many of the uses of data that create direct value don't necessarily involve a market transaction or cannot be measured by a market transaction. Volumes of data can be integrated in a way to produce creative patterns or insights far beyond the original intended purpose of data collection. For example, mobile data holding information about how individuals move, inferring where they live, their socioeconomic status and what they do.

Genuine consent is hard to achieve and it does not align with the adequate protection of individuals' interests. Disclosure of only simple information is not enough, while long or complex is unlikely to be read nor understood. The modern microeconomic theory of privacy suggests that consumers may not be able to act rationally when facing privacy trade-offs. An example of this is that most data transactions between users and online service providers are characterized by the asymmetry of information. Consumers have incomplete information about which behavior is being monitored and utilized, 'take it or leave it' offers of service in exchange for personal data, or manipulation of immediate gratification in order to marginalize future risks (Acquisti, 2013). Profiling is done to manipulate a consumer towards a product or service that the consumer may not even need, or that is not the best choice or in the best interest to purchase.

In this fast-moving data landscape, actual existing data governance organizational and technical means are pressured to provide public trust when it comes to concepts of data privacy, ownership, and consent.

For example, data about data is referred to as its metadata - and is one of the major data governance concepts. As data sets are copied to new systems, firms or countries while metadata accompany it, an audit trail of context, meanings, formats, validation parameters, and collection date can verify the authenticity or other property. Developments in privacy enhancing technologies move towards control on to selective protection or disclosure of personal information (Acquisti, 2013). Drexl (2016) confirms that factual control of data supported by technical protection measures allow data holders to exclude third parties or charge them a price for making data available.

3.6.2. DATA REGULATIONS, OWNERSHIP AND CONTROL ECONOMICS

This section extends the dialogue on the complexity of the existing economic and regulatory environment, driven by the data economy.

The microeconomic theory of protection of personal data and theory of information asymmetry (Akerlof, 1970) argues that privacy protection could increase and decrease economic efficiency, containing costs and benefits for both individuals and their data processors (Acquisti, 2013).

In choosing the sense of balance between sharing or protecting personal information, individuals and firms face complex and uncertain trade-offs, and as the market equilibrium will not provide privacy protection to individuals, regulation is therefore needed (Acquisti, 2010). On the data holders' side, in absence of regulatory intervention, it is unlikely that firms will incur the costs to transition to technologies that may, in the short run, limit their access to consumer data relative to their competitors (Acquisti, 2013). The current situation may be reinforcing the market dominance of major firms which use personal data, making it harder for new players to join the market (Alonso, 2014). As argued by Stucke & Ezrachi (2016) companies are increasingly adopting business models that rely on personal data as a key input. A company with a large base of users is able to collect more data to improve the quality of the service and, in this way acquire new users – 'user feedback loop'. These interminable loops can make it very difficult for any entrant to compete against an incumbent with a large base of customers. The winner not only gains potential revenue but possession of more users' data also helps to be a leader in improving the quality of the product itself. The dominant platform may not do anything that can be properly qualified as anticompetitive, and yet the feedback loop can reinforce dominance and prevent rival platforms from gaining customers (Capobianco, 2016).

Data-driven predatory behavior appears in the form of strategies to raise entry costs, limit competitors' timely access to key data, prevent others from sharing data, inhibit data-portability or exclude rivals that threaten the data-related competitive advantage of an incumbent (Capobianco, 2016). This requires the intervention of authorities. Gellman (2002) posits that unrestricted trafficking in personal information is always costly for the consumer.

On the other hand, Rubin and Lenard (2009) argue that regulation should be undertaken only when a given market for data is not functioning properly. Technical, legal, structural and perceptual blocks cause the most useful data to be still sealed in proprietary corporate silos, even though the value through its sharing and trading is clear. The legal framework for the secure trading of data sets is a prerequisite. Proprietary data 'owners' must have legal, organizational and technical means for sufficient confidence that they can retain control of their data and rights once unlocking data.

Conversely, Noam (1997) argues that whether or not a consumer data will remain protected does not depend on the law, rather on the level of the perceived value of privacy versus offer of the data collector. (Brunk, 2002) talks about a privacy paradox: people, in fact, are keen to unveil sensitive information for even small rewards. Data subjects can receive tangible rewards such as discounts, or intangible rewards such as personalization and customized services, even given to third parties to improve services there also. For Stigler (1980) privacy protection lowers the quality of information, and an analysis of personal information, when shared, reduces inefficiencies and increases economic welfare.

Additional costs highlighted by Samuelson (2004) comprise the social losses due to incoherent privacy policies. Amidst a complex array of legislative initiatives, both consumers and firms are uncertain about the level of protection. This uncertainty is costly in itself, as it leads that both data subjects and data holders to inefficiently under- or over-invest in data protection. Economists are generally inclined to think that well-specified property rights reduce transaction costs and uncertainty and thereby increase the efficiency of markets (Duch-Brown, 2017).

A debate over who owns our personal data can start with the fact that data is often perceived as the 'currency' paid for so-called 'free' services on the internet. The assumption that underpins the intellectual property approach is that data production has a cost and requires a financial incentive in order to stimulate investment in data collection, storage, and analytics. If they are not a public good, that would take away incentives for private agents to invest in their production (Duch-Brown, 2017). This would incur high implementation costs for small businesses especially. On the other hand, Kerber (2016) observes that there is no evidence of an incentive problem regarding the production data. Koutroumpis et al. (2016) state that data, however, are rarely final goods and are mostly intermediary goods that are used in production processes by other parties.

For Duch-Brown (2017) the important question is not who owns the data' but 'who owns the means of analysis'. Consistent with that is the work on the monetization of aggregated sensitive data (Piotrowska A.M., 2016). An interesting alternative route could be considered, in which the regulatory framework would maximize accessibility to data by any entity capable of generating value from it (European Political Strategy Center, 2017).

Heverly (2003) argues that we must examine to what extent is the right to control data - to use, to exclude access or to transfer rights - as defined by law. Organizations that hold large amounts of data may have a vested interest in keeping that data for themselves and under their control (as a competitive advantage) rather than enabling user control.

Accordingly, some economists have also proposed a 'propertization' of privacy where individual literally sells her own personal information into a marketplace or attempts to buy back the right to keep that data private (Varian, 1996). More recent works are on different models for quantifying the value of personal data (Malgieri & Custers, 2017) and on personal data usage licensing (Popescu et al., 2016).

More recently, the World Economic Forum proposed the concept of a data bank account. In the document from The Economist (2017), it is suggested that a person's data should reside in an account where it would be controlled, managed, exchanged and accounted for.

The Personal Information Management System (PIMS) is a concept to transform the current provider centric system into a system centered on individuals able to manage and control their online identity. The principle here is not about selling personal data, but rather, allowing third parties to use personal data, for specific purposes, and specifics periods of time, subject to terms and conditions identified by the individuals themselves, and all other safeguards provided by applicable data protection law (Thomas, 2016).

Exclusive ownership rights turn data from common property into private property (Fennell, 2009). This then gives incentives to the data owner and will reduce interoperability. Market faults would also be a result as citizens do not understand the conditions of data use existing in the market nor differences between the various privacy policies for equivalent services (Athey, 2017).

Economies of scope in the aggregation of datasets cannot be realized when ownership is fragmented and this leads to under-utilization of data (Duch-Brown, 2017). Full ownership grants an exclusive monopoly right on the use of data and the owner could decide not to sell his data. Cutting the data supply results in a revenue loss for the upstream supplier and demotivation for the downstream supplier to maximize investment in his service, as per the anti-commons model (Schulz, 2002).

3.6.3. DATA REGULATIONS, PORTABILITY, APIS, AND OPEN DATA

This section complements the discussion on the complexity of the existing economic and regulatory environment, with the concepts of portability, open data and application programming interfaces (APIs). They are seen as core elements of data-driven and interoperability-driven compliance regulations.

Rather than the definition of ownership rights, a more promising avenue to address issues concerning the fair distribution of value across the value chain - can be 'increasing competition at the data service level'. In the publication from the European Political Strategy Center (2017), it is claimed that competition can be stimulated through portability, i.e. by ensuring that data is easily transferable from one service to another by their users.

Klemperer (1995) argues that, in a standard market setting, portability lowers switching costs - and that in turn should promote competition between these online services. Data portability could also imply adopting different strategies or changing business models; for instance, offering better quality or customer care to avoid excessive customer churn (Rochet & Tirole, 2003). In an online platforms environment, indirect network effects are strong. Reputation depends on the number of transactions and a move to a different marketplace is not comparable (Masanell, 2009). Small start-ups might not be able to develop expensive software codes to enable the transference of data to other companies (Capobianco, 2016).

That is why there is another option - that the competition can be stimulated through the design of a regulatory framework that promotes interoperability of platforms, for example through open application programme interfaces (APIs). Europe is again the leader in this area as the first regulation that promotes this is the European Union Payment Services Directive Revised (PSD2).

As a result of their role in law enforcement, governments, public agencies, and state-owned enterprises have a privileged position to collect data that cannot be easily obtained by the private sector. This involves the provision of public services and collection of official statistics, making the public sector one of the most data-intensive sectors in the economy.

Private companies will not be able to compete against a government controlling such volume and variety of data across the whole economy, which could never be replicated by any other agent. This may be an important measure to preserve competitive neutrality and improve efficiency in the use of existing data. Governments could allow open access to some public sector information to the private sector. This could provide companies with the opportunity to innovate, prevent public agencies from forming governmental monopolies, and promote more vigorous competition by reducing the data gap between incumbents and small start-ups (Capobianco, 2016).

3.6.4. EU GDPR

Finally, this section gives a short list of details on GDPR, where this research applied explorations on the economics of data, levels, and aspects of utilized benefits associated with their economic potential and organizational practices to support trade-offs.

The General Data Protection Regulation (EU) 2016/679 is a regulation in EU law on data protection and privacy for all individuals citizens of the European Union (EU) and the European Economic Area (EEA). As per the official regulation document (2016), GDPR regulates the processing and use of personal data in the EU (EU Commission, 2016).

A single set of rules will apply to all EU member states. Each member state will establish an independent supervisory authority to hear and investigate complaints and sanction administrative offenses (Krystlik, 2017).

GDPR represents a first milestone to creating a data-friendly environment where citizens and companies feel confident that their privacy preferences are protected, while also safeguarding economic interests and innovation. GDPR entered into force on 25 May 2018, laying down the starting rules for some of the dilemmas mentioned in this research, but needs to be further complemented, developed and continuously updated.

From the 25 May 2018 date onwards, national legislation on data protection and data flows (concerning personal data) will become obsolete and replaced by the harmonized and unified regime of the GDPR. Many see this as a major milestone to overcome Europe's heavily fragmented data regime, which some argue has been a major impediment to building up sizeable companies in this space. This new, Europe-wide data framework is long overdue and has the potential to yield significant benefits, providing, for the first time, a unified, common data regime for all of the Member States. Applying data regulations at the national level would reintroduce fragmentation and therefore slow down data flows. Only a truly unified, agile and user-friendly legal framework can be the much-desired game changer for Europe's data economy (Duch-Brown, 2017).

Superseding the Data Protection Directive 95/46/EC, the regulation contains provisions and requirements pertaining to the processing of personal data of individuals (formally called data subjects in the GDPR) inside the EEA (EU Commission, 2016).

Companies processing the personal data of data subjects in the EU need to review their existing policies, procedures, and practices to ensure compliance with this new regulation as GDPR includes several options, including the ability to ban processing. Controllers of personal data must put in place appropriate technical and organisational measures to implement the data protection principles (Garber, 2018).

Business processes that handle personal data must be designed and built with consideration of the principles and provide safeguards to protect data (for example, using pseudonymization or full anonymization where appropriate), and use the highest-possible privacy settings by default (Perry, 2019).

No personal data may be processed unless it is done under a lawful basis specified by the regulation, or unless the data controller or processor has received an unambiguous and individualized affirmation of consent from the data subject. The data subject has the right to revoke this consent at any time (Krystlik, 2017).

A processor of personal data must clearly disclose any data collection, declare the lawful basis and purpose for data processing, and state how long data is being retained and if it is being shared with any third parties. Data subjects have the right to request a portable copy of the data collected by a processor in a common format, and the right to have their data erased under certain circumstances.

Public authorities and businesses, whose core activities centre around regular or systematic processing of personal data - are required to employ a data protection officer (DPO), responsible for managing compliance with the GDPR. Businesses must report any data breaches within 72 hours if they have an adverse effect on user privacy (Perry, 2019). Most explicitly, under several circumstances, the supervisory authorities can issue an administrative fine up to 20,000,000 EUR, or in the case of an undertaking, up to 4% of the total worldwide annual turnover of the preceding financial year, whichever is higher.

The GDPR was adopted on the 14 April 2016. and became enforceable beginning the 25 May 2018. As the GDPR is a regulation, not a directive, it is directly binding and applicable, but does provide flexibility for certain aspects of the regulation to be adjusted by individual member states.

Enterprises typically initiated and they still operationalize an ongoing GDPR data management program that may consist of (Krystlik, 2017):

- Projects that can help discover personal data and map data flows. Data governance technologies support auditing and data transparency policies by providing data lineage, asset inventory, and data discovery among other capabilities.

- Data enrichment in order to consolidate customer data to get a single view of the data subjects across the organization.

- Improvement of data availability and performance. Addressing the ability to restore the availability and access to personal data in a timely manner in the event of a physical or technical incident"

- Enforcement of policies and controls that are designed to protect people, software, and systems. Predictive, preventive, detective, and responsive governance and security controls across data management, identity and access management, monitoring, and user behavior analytics.

- Effectively building in cross-functional mobilization to GDPR compliance activities by identifying privacy capabilities and touch points across the organization and establishing a structure that will drive and coordinate remediation activities.

Data stakeholders from organizations recognize this as a potential 'once-in-a-generation' chance to transform their data management practices. After years of trying to get organizations to recognize the explosive value of data, and the benefits of good data management practices, GDPR can be a compelling business driver (Garber, 2018).

GDPR provides strong drivers for adoption of disruptive platforms and tools and reimagines business practices that spur innovation. For example, manual ad-hoc and single pass reporting processes were usually enough for most projects. However, GDPR requires higher and more robust reporting and auditing structures to enable organizations to adequately respond to inquiries from Data Protection Authorities ("DPAs") and individuals (Perry, 2019).

Such data compliance regulation requires an enterprise approach to the asset of 'customers' data'. Multiple departments must work together to manage and continually enhance a common data set. This can then evolve into a broader effort on enterprise data as a service to support the speed and scale at which customer-facing functions will have to operate to be competitive. Addressing GDPR compliance requires a coordinated strategy involving different organizational entities including legal, human resources, marketing, security, IT, and other departments. Successful GDPR compliance cannot be achieved without a seamless and secure information strategy across the various internal and external entities. In turn, this would require well-coordinated policies and technologies (Garber, 2018). This relates to the concept of vertical and horizontal governance span, that is in the center of this research project. The goal of the study, exploration of potentially useful organizational practices, relevantly links to the statements that data protection compliance becomes more about how well business processes are organized than formally giving and getting an authorization to process data.

3.6.4.1. ADDRESSING GDPR COMPLIANCE USING DATA GOVERNANCE SOLUTIONS

This section summarizes key governance and integration activities that can help GDPR compliance and can be addressed with the governance programs and acquired technical governance solutions (Vojvodic, 2017).

Finding data

A major challenge for any organization is to create an inventory of all Personally Identifiable Information (PII) across the enterprise. PII can come in many different formats and types (structured or unstructured) and be stored in various locations and held in various forms. PII is not necessarily stored in transactional systems only, but in application logs, social media feeds, web analytical systems that capture customer journeys through the website, customers call records.

GDPR implies knowledge of the location of all relevant PII to provide effective data discovery and all information about an individual upon request (GDRP 'subject access right') or to have all data about them deleted (GDPR 'right to be forgotten'). This requires flexible platforms to dynamically handle a potentially large number of these requests, such are self-service systems that allow appropriate and easy access to online information (Vojvodic, 2017).

To support data discovery - solutions in governance programs may be used to: harvest metadata from heterogeneous tools and perform data identification through the exploration of these metadata; provide high levels of visualization in metadata and data flows, and trace data provenance and improve data trust.

Classification of Data and Linking to Data Processes

Assuming an organization has mapped all relevant PII and 'PII data flows', the next step is that metadata about identified data elements relevant for GDPR can be loaded into a governance platform and classified. Additional linkage of data elements and business process allow easy tracing of the exact data element used in specific business (data) processes. Categorization can help with managing stewardship assignments (at the category level), sub-setting by subject matter, or sub-setting by organizational structure (Vojvodic, 2017).

Each organization should establish a business glossary – a simplified version of the data catalog, abstracted for the business user. Glossary has a higher potential of usage from line-of-business stakeholders, aligns business and IT on the definitions of business terms and provides a better understanding of the data context and usage and a clear overview of responsibilities.

Establishing Control with Policies and Rules

GDPR 'accountability principle' recommends organizations to be able to show how they comply with data protection principles, including by demonstrating that they have effective policies and procedures in place. Governance tools may configure and implement or import business rules and link them to the rest of the metadata. This allows users to see all business rules related to any item. Governance solutions can also include built-in issue management with a customizable workflow. Particular events can trigger automatic issue notification by measuring published data quality results against a defined policy. With automatic assignment of issues based on their context, issue management will serve as a way of tracking the work of data stewards formally in a dashboard (Gjermundrød H., Dionysiou I., Costa K., 2016).

Risk Assessment of Data Elements and Data Processes

After identification and categorization, organizations may want to conduct a risk analysis of their data flows and, based on prioritization, implement and document control measures. The GDPR risk assessment results are also generated based upon the level of data governance control understanding, movement of relevant PII, the volume of data, data protection availability, data proliferation, and data accessibility.

Monitoring Change, Data Proliferation and Establishing Control with Workflows

In the normal course of business, PII is often moved from a known source location to another. This is the case where IT solutions exist to solve specific business challenges involving transferring PI data to new locations for further analysis. Continual monitoring would assist organizations in discovering and capturing these transfers. Governance policy definition, automated discovery, and classification bring clarity on whether this newly generated source really contains relevant PII and how it is governed.

One role of governance is to set the scope of data-related change management. Governance consistently enforces business rules and policies across processes spanning functional and silos and customer interaction channels. As a part of governance driven change management, policies are being tracked and updated, through workflow, across different line-of-businesses, with business stakeholders and technical stakeholders involvement (Burlton, 2001).

Sharing and Deleting Data

Individuals have the right to request that an organization provides them with all the information held about them ('subject access right'). The right to 'Data portability' allows individuals in some cases to request that their data profile be passed to another organization. GDPR's data deletion or 'right to be forgotten' requirements require organizations to remove all relevant individuals' PI from their systems upon request in some circumstances. Beside data location discovery, governance solutions help organizations implement policies and rules to govern all these processes, and can profile, audit, cleanse, parse, standardize, transform, and de-duplicate all this data.

Creating a Single View of Customer

Finding all relevant PI is not always an easy exercise. Creating a single customer view is therefore considered to be a key component of a GDPR compliance framework. Bringing silos of data together in an operational data hub reduces the risks associated with not being able to find the data within the prescribed timeframes. It also helps achieve commercial long-term benefits from a 360-degree view of all individuals who interact with an organization.

Governance solutions can track the source of customer attributes, profile, audit, parse, and standardize, create a single record from multiple sources using configurable "survivorship" rules, cleanse addresses via open interfaces with address cleansing providers, and identify and eliminate duplicates (Chuck Ballard, Trey Anderson, & Dr. Lawrence Dubov, 2013).

Application Services Governance and Process Governance

The more data is being reused without proper data governance, the greater the risk of data-handling mishaps, including data accuracy and data integrity issues. Applications on the top of data management - contribute to further data and process abuse, if not approached with proper governance. Governance of application services and business processes increase the capability of process owners to provide the subject matter expertise required to understand the meaning of data within the context of their processes (Rosing, Scheel, & Scheer, 2014).

Using governance of application services and governance of business process management it is possible to: integrate all GDPR requirements into process landscape all controls, involve stakeholders and all employees using policy management, create incident procedures and handle incidents (breach notification may be an integral part of the privacy incident processes), support consent via the design of the GDPR processes and records management, capture data transfers as processes. Generated audit trails provide factual and objective governance accountability – information about who and why did exactly what.

4. RESEARCH MODEL

This segment of the dissertation covers the research model and an overall conceptual framework, including construct conceptualization methodology. Furthermore, it details hypothesized relationships between the constructs of this quantitative research.

4.1. CONCEPTUAL FRAMEWORK

The argumentation provided in the theoretical background section leads to the hypotheses listed below. The hypotheses are divided into two parts: primary hypotheses (marked with asterisk *) that primarily guided this research, and secondary hypotheses that are included due to the exploration-driven nature of this study.

H1: Customer-Centric Orientation (CCO) 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 of Privacy Project Efficiency (PPE).

Data Governance Span (DGS) is a higher order construct consisting of two lower order constructs: Line-of-Business Stakeholders Participation (LOBSP) within Data Governance Span and Cross-Functional Integration (CFI) within Data Governance Span.

H4: There is a mediating effect of Cross-Functional Integration (CFI) on the Customer-Centric Orientation (CCO) - Line-of-Business Stakeholders Participation (LOBSP) (CFI) relationship.

H5*: Governance Teal Leadership (GTL) leads to an increase of Line-of-Business Stakeholders Participation (LOBSP).

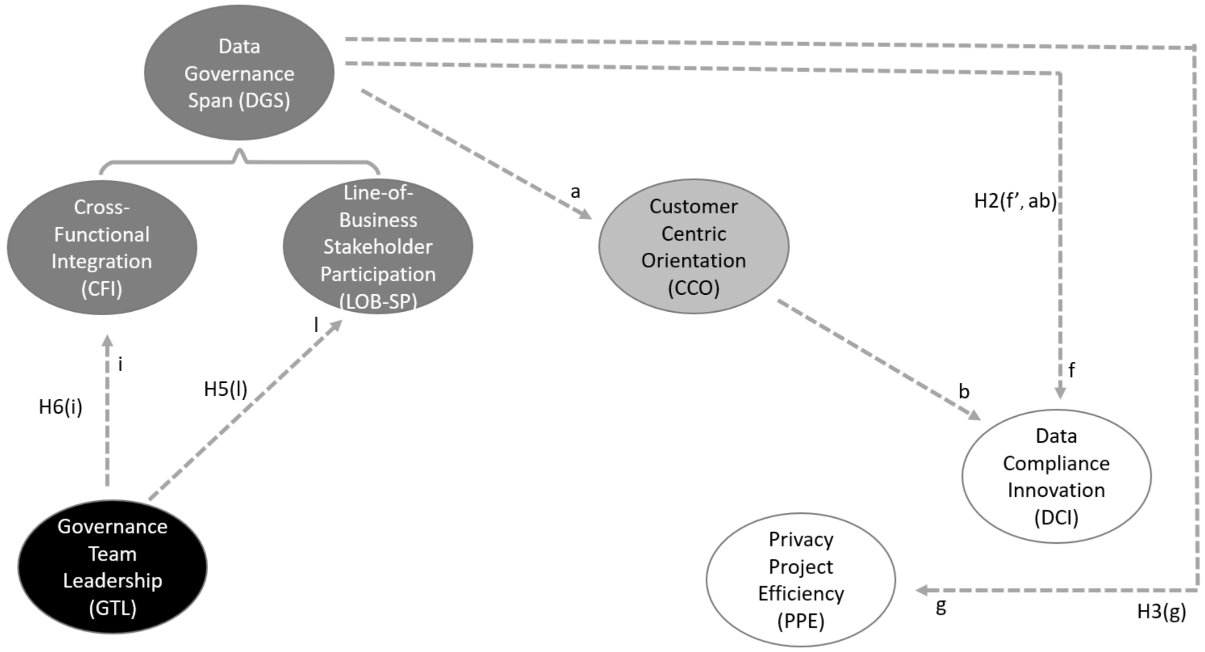
H6*: Governance Teal Leadership (GTL) leads to an increase in Cross-Functional Integration (CFI).

H7: There is a mediating effect of Line-of-Business Stakeholders Participation (LOBSP) on the Governance Teal Leadership (GTL) - Privacy Project Efficiency (PPE) relationship.

H8: There is a moderating effect of Line-of-Business Stakeholders Participation (LOBSP) on the Cross-Functional Integration (CFI) - Privacy Project Efficiency (PPE) relationship.

H9: There is a mediating effect of Cross-Functional Integration (CFI) on the Governance Team Leadership (GTL) - Privacy Project Efficiency (PPE) relationship.

Figure 9: The primary hypotheses research model



Source: Author

In order to achieve an easier visual overview, the hypotheses are graphically represented with two different model sections:

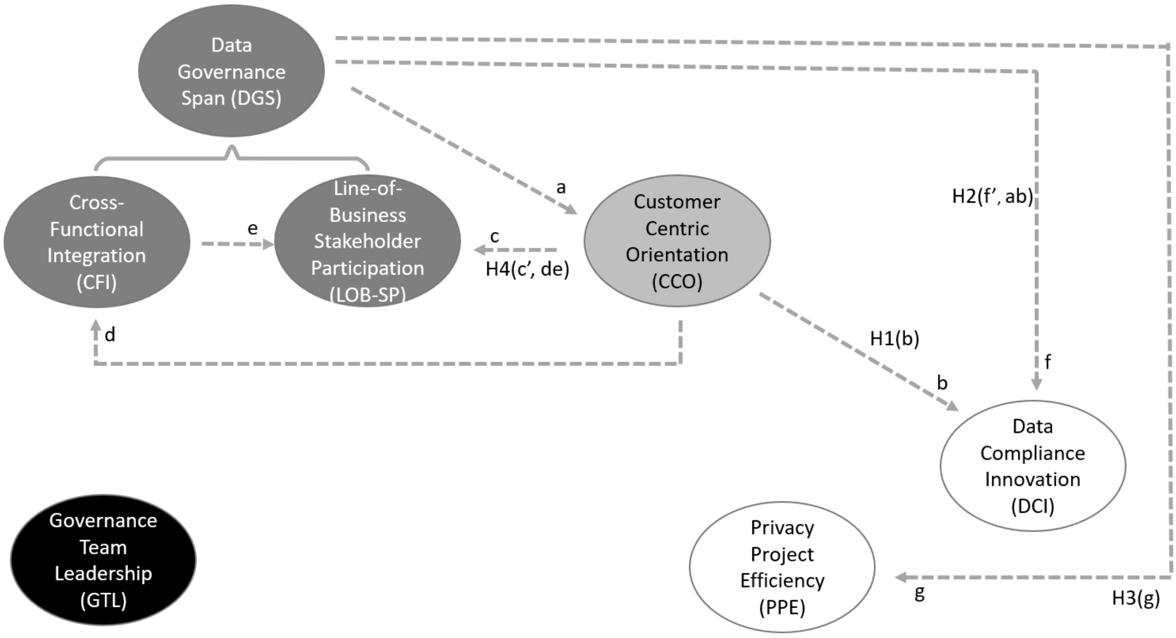
Model section A (Figure 10): Relation between Customer Centric Orientation (CCO) and Data Governance Span (DGS) and its lower order constructs. The relation between Customer Centric Orientation (CCO) and Data Compliance Innovation (DCI) belongs also to this area.

Hypotheses are H1, H2, H3 and H4.

Model section B (Figure 11): Relation between Governance Teal Leadership (GTL) and Data Governance Span (DGS) and its lower order constructs. Relation of both with Privacy Project Efficiency (PPE) also belongs to this area.

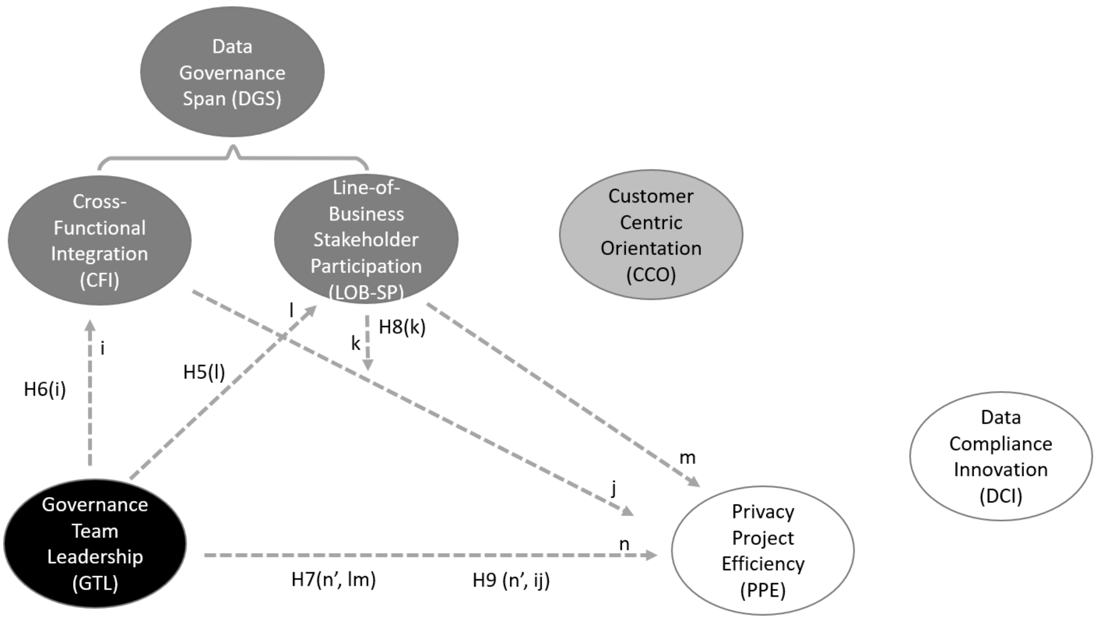
Hypotheses are H5, H6, H7 and H8 and H9.

Figure 10: Full research model – section A



Source: Author

Figure 11: Full research model - section B



Source: Author

4.2. CONSTRUCT CONCEPTUALIZATION

The relationship between concrete, observed measurement hypothesized to measure the concept and an abstract, unobserved concept is the hypothetical measurement. Such a relationship is partly logical, partly empirical, and partly theoretical (conceptual), where the factor loading represents itself only part of the empirical meaning of such relationship (Bagozzi & Yi, 1988). As stated by Wright et al. (2012), constructs are just efforts to describe real phenomena, and there is a measurement error that exists as a gap in these efforts to provide complete accuracy while capturing phenomena. Some constructs may prove continuing usefulness, while others initially considered useful may be modified or abandoned as knowledge accumulates (Messick, 1981)

With the aim to minimize the coverage of any concepts outside of the focal construct domain, construct items were generated and assembled inductively. Reviews of the literature and previous theoretical and empirical research on the focal construct were combined and deduction with preliminary research using the inductive approach was done in cooperation with subject matter experts and professionals as well as experts in the field (Churchill, 1979). This research used both inductive and deductive methods in construct and items development. 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). Schwab (1980) describes that item development can be deductive or logical partitioning, where a detailed review of the literature and theoretical definition of the construct is then used as a guide for the development of items. It can be also inductive or grouping where there is not enough theory involved and the only way to identify constructs and generate measures is from individual responses (Hunt, 2016).

This research went through the process of construct conceptualization and re-conceptualization for all of its variables. Three steps were followed in the process. It was first examined how the focal construct (or related constructs) have been used in prior theoretical and empirical research (or used by practitioners). Second, the conceptual domain of construct was rationalized - following the nature of the construct, the type of property the construct represents, and the entity to which it applies (for example, an organization or firm was an entity in all five constructs). Third, the specification of the conceptual theme received the construct unique attributes and characteristics.

In order to uniquely attribute and assign characteristics to the constructs, the second review of existing definitions of the literature was conducted. Special attention was paid to those definitions developed in organizational sciences, strategic management, organizational psychology or marketing, as well as the repetitive common usage of the terms. Therefore, constructs used in the model were derived from intersecting previously highly cited references that exist in the body of knowledge of different theories.

To develop the constructs, the guidelines of Diamantopoulos and Winklhofer (2001) are followed. In terms of content specification, new scales for constructs were developed in order to ensure that the indicators covered the entire scope of the respective construct. An extensive literature review formed the basis for the specification of the content of the focal constructs. General findings are that literature highlighted the importance of construct; however, they did not measure it.

Despite the evolution of the concepts used in this research, inconsistencies in the multiple business definitions of data governance have been further manifested in the existing research in its treatment of concepts of data governance span, team leadership, cross-functional integration, line-of-business stakeholders' participation. In the theoretical background section, it is thoroughly justified how the literature review led to the emergence of the final dimensions used in this research.

Although the conceptual discussion in the theoretical background section shows that there is a range of different dimensions of data governance, the current research employs Data Governance Span as categorical higher order construct which consists of two sub-constructs: Business Stakeholders Span and Cross-Functional Span. The examination of previous research also guided the classification of the data governance dimensions into two higher categories: vertical (business stakeholders span) and horizontal (cross-functional span). This decision came from the necessity to distinguish between the first level of abstraction, which relates distinct indicators to each dimension (first-order), and the second level of abstraction, which relates dimensions to the construct (second-order) (Edwards, 2001). The single theoretical concept that is measured by several associated constructs is a multidimensional construct that allows researchers to create theories about the relationships of complex multipart concepts (Law, Wong, & Mobley, 1998). These constructs are more theoretically useful than their dimensions. Newman et al. (2016) argue that theories require general constructs that combine specific dimensions in order to be general themselves. On the other hand, the 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). Governance team leadership (GTL) integrates stakeholder theory with change management, and resistance to change with leadership theory. Data governance stewardship team members need to have a high team identity and some of the transformational leadership abilities for an efficient span of governance, considering change resistance in such projects.

Following the need for leadership addressing change management resistance, two concepts were taken that intersect with leadership theory as two sources of the team leader's effectiveness: power/influence via emission of strong cross-functional team identity and transformational leadership and behavior via communication and knowledge sharing. This is just a small subset of potential behavioral or influence driven leadership strategies. 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 governance-driven projects that required efficiency. Accountability was distributed across operational data stakeholders in all functions, including line-of-business stakeholders. 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.

The constructs research models are reflective. They are seen as manifestations of a focal construct and construct sub-dimensions imply the usage of reflective constructs in such cases (Bollen & Lennox, 1991; Jarvis, MacKenzie, & Podsakoff, 2003). Additionally, this research notes causality that the change in the focal construct produces a change in construct sub-dimensions which is characteristics of reflective constructs. In this way, constructs are seen as causes of measures (Bollen & Lennox, 1991). Reflective indicators for each factor share a common theme and are expected to be correlated and interchangeable, which is the case in this study. As such, removing one of the indicators will not change the conceptual meaning of the factor. Formative indicators do not necessarily share a common theme and consequently are not necessarily correlated, nor interchangeable and eliminating one of them could potentially shift the meaning of the factor (Law et al., 1998). Constructs are not inherently formative or reflective in nature, and most can be modeled as having either formative or reflective indicators depending upon the researcher's theoretical expectations (Bollen & Lennox, 1991).

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), and all operational definitions specify the construct's conceptual theme consistently with prior research and in clear terms, distinguishing it from related constructs (Jarvis et al., 2003).

4.3. PRIMARY HYPOTHESES

The hypotheses of this research are divided into two parts: primary hypotheses (marked with asterisk *) that primarily guided this research, and secondary hypotheses that are included due to the exploration-driven nature of this study. H2, H3, H5, and H6 are primary hypotheses covered in this section.

4.3.1. H2: DATA GOVERNANCE SPAN (DGS) --> DATA COMPLIANCE INNOVATION (DCI)

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 is 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, 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). 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, 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. Data compliance regulations can be a platform for the creation of new business propositions for customers in order to increase internal return on investment in such data. At the same time, they can add more value when reverting these data back to customers and provide innovation in the increased dialogue with consumers (Hahn et al., 2018; Myles, 2015).

Governance has been used to improve the internal and external value of the channel of communication with customers for a long time. Nguyen et al. (2014) outline that only trustful, traceable and an authoritatively detail-level of data management allows an immediate collection of response from customers in an optimized and central point of data collection, driving engagement of new customers, and further targeting and re-engaging existing ones. The entire life cycle of online and offline data on analytical scores, web behavior data, campaign response data and customer profile data and offline customer transactions if centralized and authoritative can be applied and delivered to customer based on their specific browsing and purchasing habits to further enhancement of the customer experience across all channels (Gregory & Bentall, 2012). Good examples to illustrate the internal application of governance are strategic and organizational improvements of customer data, master data management projects that are intimately related to data governance (Loshin, 2010), and the establishment of roles for planning, designing and overseeing MDM activities. These are typically governance roles held by the data owner and data steward (Khatri & Brown, 2010).

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 (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 those customer-centric units that aim to increase the relationship with, and experience of, a particular customer. King and Forder (2016b) add that this generates new ideas on revenue generating customer engagement. Innovation on top of customers' data requires a single view of customers.

A prerequisite for this is governance processes with a vertical and horizontal span that help to discover and resolve inconsistencies and incompleteness caused by different business units. Different business units often use the same data attributes to describe different entities. Data attributes that describe business entities (product names, total revenue) often contain different values for the same attributes across different applications and lines of business. Data relationship inconsistencies impact the ability to identify relations between business entities (for example, accounts and payments, customers and households, and products and suppliers). These relationships are often defined differently in different applications and across lines of business (Berson & Dubov, 2011).

For innovative decisions from line-of-business stakeholders on the top of data, it is necessary to trust in the information system underneath. The 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. Governance becomes a driver of increased information flows within the organization (Leenheer et al., 2010). Line-of-business stakeholders become more appreciative of the system, having a higher belief about the relative value of the system. This increase in appreciation translates into an increase in the use, leading to innovation and an even greater appreciation of the system.

Trust in the system needs to be supported with good data quality, ensured by governance. Existing IT-driven concepts of data quality do not include the business view of data quality management and therefore lack the strategic orientation in its measurement (Otto, 2011a). The value of improved data quality is almost self-evident and includes factors such as the enterprise's ability to make better and more accurate decisions, to formulate a better and more effective marketing strategy, to define a more attractive and compelling product, to gain deeper insights into the customer's behavior, to understand the customer's propensity to buy products and services, the probability of the customer's engaging in high-risk transactions, the probability of attrition, and so on (Seiner, 2014). Information can be gathered from customers, and then also needs internal information processing capabilities in order to channel externally collected information to the most appropriate internal stakeholders.

Communication brings creativity and innovation and cross-functional integration is encouraging communication between different functions (Gatignon & Xuereb, 1997). Montoya-Weiss et al. (2001) claim that it is the strength of interaction and communication - the level of information sharing, the degree of coordination, and the extent of joint involvement across functions in specific tasks - that increases both communication frequency and 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.

Functional diversity can also increase decision complexity and confusion (Rajesh Sethi, 2000). Tidd (2001) stated that cross-functional teams have more to offer than individuals in terms of idea generation flexibility to solutions developed, and a mechanism for bridging boundaries to create innovative solutions within organizations. Cross-functional teams provide a substantial range of ideas, !earnings and improvements that can be applied to the organization. Cross-functional teams can reduce misunderstandings that arise in the different values found within functional areas if the cross-functional team members are able to develop a shared language and shared mental models. By doing this, actors from different functional areas can share information at all stages of the implementation of technological innovations such enterprise information systems, making it easier to identify problem areas early in the process and finding solutions that are shared by the team members in the same language (Santa et al., 2011). In cross-functional teams, people tend to reach further and faster to gain or spread knowledge (Robbins, 2003). Boundary spanning agents are viewed as communication stars (M. Tushman & Scanlan, 1981).

Wang and He (2008) suggest that incorporating interdependency among team members into a cross-functional team yields positive functions and takes into account the social benefits generated from team interactions for both firms and individual employees. Establishing cross-functionally integrated teams that focus on developing and implementing a consistent strategic vision is practical to meet ever-changing demands. Cross-functional integration is essential for providing and processing quality information and developing effective decision-making processes (Pimenta et al., 2016). 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 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, Chew, & Fujimoto, 1987), and provides cross-functional perspective sharing that also supports innovation (Clark et al., 1987). As a source of creativity, 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 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).

4.3.1.1. MEDIATING ROLE OF CUSTOMER-CENTRIC ORIENTATION

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, knowing that decisions being taken are based upon the best data available. Operating within the customer-centric model requires ad hoc trustworthy, relevant, consistent and timely information about customers.

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). It is necessary to do more than that and look around for deep and unusual insights that anticipate trends and changes (W.

Kim & Mauborgne, 1997). An organization must also identify new products and services to offer before existing customers even think of them (Prahalad, 2016).

Jaworski and Kohli (1993) and Day (1994) argue that market orientation delivers strong norms for sharing of information and reaching a consensus of meanings with functionally coordinated actions of customer-facing units engaged at the realization of competitive advantage. Low formalization as a result of customer-centric organizational integration leads to a higher capacity to innovate (T. Burns & Stalker, 1994). Autonomy and flexibility in roles is a condition for the initiation of new ideas. Enterprises with a flat hierarchy in their structure are more innovative (Jaworski & Kohli, 1993), as they are sharing expertise and they have more open and frequent communication, with a tendency to focus on results (McGinnis & Ackelsberg, 1983). Imai et al. (1985) claim that market intelligence, with external orientation and communication, networks, and involvement with suppliers and customers facilitates innovation. Day (1994) supports the idea that environmental scanning provides an opportunity to act proactively. The sharing of market information in the organization enhances market responsiveness (Jaworski & Kohli, 1993).

Likewise, a strategic innovation culture could be achieved by flexible organizational boundaries, broken functional silos, a bit disordered workplace with freedom of ideas and creativity, and with quick-changing cross-functional project teams (Schlegelmilch et al., 2003). Strategy discussion across all functional and hierarchical boundaries leads to a diverse and deeply participative process that leads to innovation and strategy success, as illustrated by several scholars (S. Floyd, 2018). Krinsky and Jenkins (1997) recommend that representatives from R&D, sales, marketing, finance, and other key functions 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 (S. Floyd, 2018).

Shockley-Zalabak et al. (2010), attribute organizational trust as expressed by a specific organization's culture that comes from highly collaborative environments. Colquitt et al. (2007) outline that trust provides higher tolerance for errors and risk-taking, and encourages participants to generate and share new ideas, which is a prerequisite for innovation processes. Trust facilitates knowledge sharing (Chowdhury, 2005), which in turn increases innovation processes (Darroch, 2005). 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 cross-functional 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).

The behavior of operational data stakeholders is not completely self-determining. It comes as an outcome of a mix of mutual influence and interactions (Frooman, 1999). Integrative organizational structures of customer-centric models clarify interdependencies and build information processing capabilities. Internal integration, however, provides mechanisms to afford efficiencies through greater immediacy and breadth of information processing. Integration mechanisms serve to automate or eliminate cross-departmental transactions and data translations. Similarly, this reduces another process waste associated with functional silos where involving various stakeholders is not so streamlined a process (Swink & Schoenherr, 2015).

As a customer-centric dimension, information integration allows an organization to understand the factors and trends that may affect the business, gain better insight into the customers' goals, demands, abilities, and their propensity to request additional products and services, thus increasing the cross-sell and up-sell revenue opportunities, and offer a rich set of personalized services and appropriate treatments. These factors lead to improved customer experience and reduced customer attrition, and a better understanding of the totality of the relationships it has or may have with the customer (Berson & Dubov, 2011). For most customer-oriented units, the ability to deliver the right personalized content cross-device and cross-channel is the most favored segment of the process that builds value-added customer engagements across all digital channels and utilizes an automated strategy to re-engage users throughout their journey. 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 the strategy of strengthening the customer dimension of the organization and assembling well-functioning innovation and consultative selling teams in order to increase the relationship, along with consultative competence selling with particular customer or customer groups, leads to greater leverage in the existing knowledge of the data about customers that lies within its line-of-business and integrates this knowledge.

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).*

4.3.2. H3: DATA GOVERNANCE SPAN (DGS) --> PRIVACY PROJECT EFFICIENCY (PPE)

This research suggest data governance span (DGS) consists of vertical (business stakeholders span) and horizontal (cross-functional span), and that the formal engagement which assumes line-of-business stakeholder participation responsibility and formulation of objectives, evaluation of results and use of output is related to the former, while the sharing of information and ideas between functions and cross-functional communication to resolve data issues is related to the latter one. Establishment accountability for customer privacy protection is one of the governance-driven projects that required efficiency (privacy project efficiency - PPE). Accountability was distributed across operational data stakeholders in all functions, including line-of-business stakeholders. Identifying any gaps or overlaps in the data lifecycle such as missing necessary responsibilities assigned to line-of-business stakeholders or other operational data stakeholders was one of the major governance related projects conducted by every company that aims to comply with the regulation. In bigger enterprises, it is led by a data governance stewardship team.

Accountability is the assignment of decision rights and responsibilities pertaining to data management; appointing people in data management roles, empowering them in those roles, and consolidating and managing all enterprise-wide data governance efforts (Kamioka, Luo, & Tapanainen, 2016). Information governance is defined as the formal framework with structure and execution of authority and accountability over information assets, created in order to encourage, enforce, and monitor meeting the desired organizational objectives (Khatri & Brown, 2010) (Seiner, 2014) (Weber et al., 2009). Data governance enables the organization to manage its data as a corporate asset, for which the entire enterprise has collective ownership and shared responsibility, but that also requires individual accountability for specific roles (Harris, 2011).

Literature suggests that accountability is a key aspect of data governance when it comes to aligning the whole program with business stakeholders. Management of stakeholders is a major element dictating project success as noted in the literature (Lycett, Rassau, & Danson, 2004) (R. Freeman, 2010). Integration of the stakeholder theory has increasingly been seen in project management studies (Lycett et al., 2004). The work of Jonas (2010) focuses on identifying the key roles of project management process and assigning their targeted responsibilities. Rowyley (1997) researched the mobilization of stakeholder groups and evidenced that the identity of a stakeholder and its interest impacts the intensity of stakeholder action. Similarly, Frooman (1999) recorded that stakeholders are able to influence other stakeholders and thus indirectly increase project success. This was confirmed by Beringer et al. (2012). 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).

Grojean et al. (2004) claim an important role of management practices in creating a culture of compliance for IT processes within an organization. This can be seen as the focus of amount of academics Business stakeholders send messages to employees that inevitably shape the culture of their organizations (Beyer & Nino, 1999), aligning with wealth creating perspectives of governance (Filatotchev, 2007). Feurer et al. (2000) add to this that as user participation drives the perception of belonging and empowerment then the project is more efficient and the resource support process is leaner if line-of-businesses work closely with the project team. Muller 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 gaps in information systems. All these responses help better prioritize decisions. There is faster team problem-solving (Sapsed, Bessant, Partington, Tranfield, & Young, 2002). 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 in development projects (Müller & Jugdev, 2012).

Cross-functional integration from a governance concept can be related to project efficiency and that was the attention of many researchers, operating with slightly different concepts. Firms merge the advantages of project coordination and functional linkages through matrix structures (R. Ford & Randolph, 2016). Cross-functionally, well-integrated teams are a factor of great impact on shortening cycle times (Griffin, 1997), and this is steadily reported in the literature. Cross-functional team members have excellent access to the knowledge and resources across different units and linking organizational interfaces is possible on the top of such flat, lateral structures (Ernst, 2002). Permitted communication flow and immediate stakeholder input are factors in the contribution of cross-functional integration projects (C. Brown, 1997; S. Brown & Eisenhardt, 1995). Rulke and Galaskiewicz (2000) note that the consequential knowledge variety of cross-functional team becomes an incubator of ideas and decisions are made much quicker as it is possible to approach any stakeholder.

Correspondingly, the cross-functional team decreases the probability of unnecessary re-work and that way speeds up the project implementation (Rulke & Galaskiewicz, 2000). Business semantics can be useful 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 (Leenheer et al., 2010). The speed of the project is increased as trust reduces the agreement making the process and simplifies the content of agreements, leaving parties with flexibility and reaction in case of changing circumstances (Bibb & Kourdi, 2004). Jong and Elfring (2010) argue that trust motivates people to do their best and not disappoint particular group agreements.

The cross-functional team is most efficient when their intention is to reach a goal that requires adaptation, speed, and fulfillment to the end-customers' related requirements (Hellriegel & Slocum, 2004). Wilemon and Cicero (1970) explain that centralization of the point of contact for any information about the project positively relates to efficiency. Likewise, Platje et al. (1994) state that if the aim is to optimize the objectives of their department or function, the effective and efficient appointment of functional employees is the duty of functional line managers, which makes them resource owners and increases their importance for the project speed.

Creativity and problem solving are improved with assembling the knowledge base from different units (Lampel, 2001). High levels of team problem-solving and quick trouble-shooting are positively related with faster project execution. A collaborative base is necessary for knowledge flow, the source should have the willingness to share (Huber, 2001) and the target must value the new knowledge and have the capability to absorb it, according to Connell et al. (2003). This directly impacts the effectiveness of inter-project learning as shown in the work of Landeata (2008). Lloyd-Waker et al. (2014) suggest that what improves project speed is actually the existence of a "no-blame culture" that leads to on-time engagement of key stakeholders, joint work to resolve unforeseen and growing problems on time and discuss them openly instead of a strategy of opportunistic behavior, and defensive behaviors when things go wrong, creation of a learning climate, willingness to learn from mistakes, load-balancing and power-distance lessening between members. The creation of a "no-blame culture" often requires first and foremost the building of trust (Mainga, 2017). Trust increases operational performance as understood in terms of quality, cost, flexibility, or speed (González-Benito, 2005), (Ellonen, Blomqvist, & Puumalainen, 2008). Dyer and Chu (2003) extend this with the explanation that a reason why trust fuels operational efficiency is the fact that trust cuts the transaction cost as there is a drop of monitoring as a form of control, the decline of enforcement and safeguards, as well as of the time and resources required for transaction fulfithe llthe ment. Trust reduces the duration of the agreement-making-process and simplifies the content of agreements, leaving parties with flexibility and reaction in case of changing circumstances (Bibb & Kourdi, 2004). It motivates people to do their best and not disappoint particular arrangements (Jong & Elfring, 2010).

MDM and data quality concepts recorded some of the initial usages of governance for the compliance and accountability across the enterprise for traditional compliance purposes, implementing clarity and control of access management and user roles as well as process efficiency. Baghi et al. (Baghi, Schlosser, Ebner, Otto, & Oesterle, 2014) state that some of the major drivers and claims in the MDM evolution turned out to be legislation on sensitive data and data privacy driving the addition of data governance and the process of roles identification, and their assignment of responsibilities for management and use of master data. MDM often requires changes, such as new practices, disciplines, methods, roles, responsibilities, policies and procedures in the organization and its operations. This becomes particularly problematic if explicit data governance roles have not been set (Tuck, 2008), (Vilminko-Heikkinen & Pekkola, 2013).

Additionally, Elgammal et al. (2012) outline that compliance reporting is based on the querying of an extensive log repository where from the behavior of different functions and roles could be monitored and data misuse could be detected driving the basic requirement for data quality accountability. The studies show that managing the data quality of enterprise data is not effective without a formal model, due primarily to the lack of clear roles and responsibilities among data stakeholders (Cheong & Chang, 2007). Examples of reporting related regulations are the international Basel II standard and the European directive Solvency II, intended to control capital banks and insurance they need to hold to manage the financial and operational risks they face where banks needed to consolidate data on all their bank accounts to show a supervisory body which of its commercial clients have over EU 100 000. This was a major time and effort consuming activity to deliver these reports to the supervisory body. Data governance was associated with MDM and data quality and used to help in setting company-wide standards for metadata, making it easier to combine datasets. MDM terminology is not shared across functions and there is an absence of commonly agreed terms leading to a lack of mutual understanding (Silvola et al., 2011).

There are various options for assigning accountability for a subset of the data from the enterprise perspective to the operational data stakeholders. One of them is through approved policy, making stakeholders become accountable for how data in their domain are managed (Seiner, 2014). If the policy is designed by a 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.

One of the central concepts of data governance is its definition, implementation, and enforcement of policies which govern the interactions between business processes, data, technology and, most important, people (Harris, 2011). Governance converts policies into practice easily, driving efficiency. A set of process maps could define and document the essential data protection processes that convert the policy into practice. Each specific process should be sufficiently documented so that anyone who has identified responsibilities within the process is clear about what has to be done, by whom, and by when, in a way that will deliver consistent outcomes (Team, 2017).

Accountability improves trust in data – and therefore increased and consistent consumption from authoritative data assets – now certified for its authenticity, which adds line-of-business stakeholders as supporters for the governance program. However, their continuous participation is necessary for their full involvement in accountability established in processes.

GDPR regulation required multi-source data discovery at its inception, including a data privacy accountability reconciliation project. Understanding of contextual explanations leads to the ability to reconcile and compile data from multiple sources, while maintaining the links to the original data as context explaining elements, further providing trusted access to data. Governance reduces the need for data transfers as the data can remain in their original destination and still be recognized and blended data (Dahlberg & Nokkala, 2015).

Governance helps to manage data associated risk, and ensure compliance with ever-growing legal, regulatory, and other requirements. This is accomplished not only by creating rules about information use but by applying and enforcing effective processes and controls to make sure that the rules are being followed (Seiner, 2014).

Formalization of the role of the data governance stewards brings productivity and leaner, more efficient flow. They answer the question once, answered ones are documented in the business glossary, leading to fewer arguments and leaner process. They become a recognized authority on the data and have the ability to make quicker decisions. The processes for changes become repeatable, with potential for automation and efficiency, as well as faster and causing far less confusion. With the formalization of this role, the individual's performance objectives can be adjusted and this expertise and responsibility formally recognized (Plotkin, 2013). Seiner (2014) outlines that one of the major tasks of the data stewardship team is recording and sharing information about changes to the data in respective domains. 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. Without data governance, even though the MDM concept ownership was explicitly assigned to the IT unit, allocating responsibility to other units was challenging. Switching responsibilities from one person to another was also difficult (Silvola et al., 2011).

Lucas (1973) argues that a more accurate and complete assessment of line-of-business requirements in the project provides line-of-business expertise about the organization the project system is to support. This is increasing efficiency of the project, as unacceptable or unimportant flows are eliminated at the start (Robey & Farrow, 1982), user understanding of the system is increased, and realistic system capabilities are known from the start (GIBSON, 1977). This leads to system ownership by users for easier organizational change through a process of open interaction and joint evaluation with faster and higher acceptance and higher quality in the change implementation (Zand & Sorensen, 1975).

One of the sources of project inefficiency is line-of-business stakeholders' lack of understanding of their roles. The root cause of poor governance of data as well as poor data quality can be traced to the lack of a shared understanding of the roles and responsibilities involved in how the organization is using its data to support its business activities (Harris, 2011). Huner et al. (2011) align with this, stating that a common understanding of business objectives leads to clarity of business processes, diminishes the occurrence of errors and reduces process waste.

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. Performance indicators that companies follow are financial ones, while others mainly are not even an integral part of the monthly or annual reporting. Improving operational effectiveness involves determining key performance objectives and establishing benchmarks.

The governance framework is based on iterations which bring efficiency. Governance brought a practical shift of understanding that MDM is not just data, rather is recurrent communication of process owners, and those who enter the data into information systems (Vilminko-Heikkinen & Pekkola, 2013). After the tasks of defining and assessing the information, the product has been completed once, familiarity with fundamental concepts and mechanisms makes it comparatively easy to repeat the work for another information product (Wang, R. Y., 1998), increasing efficiency all future activities or projects related to it.

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).*

4.3.3. H5: GOVERNANCE TEAM LEADERSHIP (GTL) --> LINE-OF-BUSINESS STAKEHOLDERS PARTICIPATION (LOBSP)

Governance team leadership (GTL) integrates governance with change management, and resistance to change with leadership theory. Data governance stewardship team members need to have two sources of the team leader's effectiveness: power/influence via emission of strong cross-functional team identity, and transformational leadership and behavior via communication and knowledge sharing. One of data governance span's lower order constructs - line-of-business stakeholders participation (LOBSP) - relates to formal engagement which assumes stakeholder participation responsibility and formulation of objectives, evaluation of results and use of output.

Business stakeholders, participation and user involvement is the factor steadily related to the quality of final outcomes of any information system (Edstrom, 1977), including governance. However, it is commonly operationalized through dependent variables such as system quality or system acceptance (Ives & Olson, 1984). Cognitive factors and motivational factors, such leadership of governance team, are seen as intervening mechanisms (Locke & Schweiger, 1979) and are not used in operationalizations.

The relationship between the impact of team identity and superordinate goals in line-of-business stakeholders' participation has been widely investigated in similar concepts. Many governance and stewardship initiatives fail to gain executive sponsorship or support due to weak team identity and lack of connection to the overall business vision. If line-of-business stakeholders do not perceive the management as supporters of the formal vision associated with the project, they are unlikely to be its followers (Pardo del Val & Martínez Fuentes, 2003). To avoid resistance, there must be top management support and the ability to obtain user involvement in the design process (Markus Lynne, 1981).

Leadership in a data governance team with a strong team identity is determined to have the detailed business justification of return on the data governance investment. To achieve compliance and to successfully implement an enterprise data governance and data quality, the strategy needs to come with a value-added business proposition (Seiner, 2014). This is how management and line-of-business stakeholders start following the vision. The fact that there is no direct responsibility for defining, managing, tracking or improving the data they use to reduce the quality of the data leads to deep-rooted silos, causing problems with data reuse and sharing, decreasing further the value of the data.

Initial reaction to the term "data governance" in siloed domains is often resistance and concern that it will include a number of laws or rules, is about command and control, and will interfere with existing responsibilities. It is an initiative over and above normal work efforts, threatening the existing work culture. This reaction will likely also reject to acknowledge or even consider the value that data governance will add (Seiner, 2014).

In such siloed cultures, both vision and organizational authority is the best way to ensure that data stewardship has to stay in power (Dyche, 2015). The data stewardship governance team should have a vision or data roadmap within the department, motivate others to contribute and to believe in the vision, repeatedly search for ways to progress from existing stage data management, and frequently suggest better ways how data are defined, produced, and used. Seiner (2014) states that data governance stewards are motivators of the practice of inclusion of all parties interested or mandated alongside the data integration process. Kelley et al. (1992) argue that if collaborating with the project team has a high level of extrinsic motivation, associated with meaningful, fulfilling and understood goals, the users will provide much more effort to build a good relationship with the team. Extrinsic motivation impacts users' devotion toward the desired objective (Sunil Ramlall, 2004). Based on 'expecting theory', extrinsic rewards are signs that a member is valuable and that plays an important role in the success of the team (Kelley et al., 1992).

The literature contains studies that can be applied to justify communication, knowledge sharing, and work structure initiation impact on line-of-business stakeholders' participation. One of the definitions of data governance is that it is execution and enforcement of authority over the management of data (Seiner, 2014), where task structure, work-scheduling, and communication from the data stewardship team can be seen as means of such execution. Initiation of structure adopts the use of rules, directives, and routines, exactly as mechanisms in integrating tacit knowledge embedded in individuals (Grant, 1996b). Hunton and Beeler (1997) worked on proving the relation between the desire to participate in the information system application and development and users' belief in their ability to succeed in certain behaviors.

Silvola et al. (2011) suggest that business process owners did not even recognize their role as responsible for enhancing the data quality associated with their own processes, while at the same time doubting their skills, expertise, and ability to contribute to the project. This self-efficiency drives their desire to confidently step in and engage in different behaviors. High self-ability encourages operational data stakeholders' engagement with expectations of meaningful work as an outcome out of it (Hacker & Roberts, 2004). Eby et al. (1999) propose that productive and self-fulfilling work consequences arise from the confidence that stakeholders have increased their participation. This can be a direct consequence of knowledge transfer, communication, and work structure initiation from the data governance stewardship team. Data governance team leaders, skilled in interaction and collaboration, would realize the importance of a non-threatening approach to data governance and carefully communicate mere comparisons to existing practices, only initially to identify and leverage strengths while addressing opportunities to improve (Seiner, 2014).

Wang (1998) provides a 'raw materials versus raw data' analogy between producing information and producing products in manufacturing. Respectively, the information product issues should not be left for consumers to recognize and resolve. The product team is proactive in communication and leadership driven. The team continuously improves the quality of the information product by expanding the team competence on how and why the consumers use information. Likewise, communication among these different roles can be effective only if information consumers also understand how information is produced and maintained. This can be applied in knowledge transfer, communication and structure initiation relation between the data governance stewardship team (producers) and operational or line-of-business stakeholders (consumers).

Different business units protect, through inertia, their own distinct data management practices and processes developed over the years. Only leadership driven changes in the organizational practices may interrupt this rigid structure. Means of data governance provide a process and structure as a platform that leadership can utilize (Vilminko-Heikkinen & Pekkola, 2017). Following a proposal from Salaway (1987), the level of extrinsic motivation and users' ability is in the very nature of the relationship between a team of users, stakeholders and data governance stewards and is a key factor that identifies and determines the outcome.

Baghi et al. (2014) argue that autonomy, responsibility, and satisfaction achieved through different task accomplishments increase stakeholders' ability to engage in system usage. Structure initiation, knowledge sharing and communication from the side of the governance team are especially important in achieving a high level of collaboration in data governance frameworks that are not easy to use and require effort for managing and maintaining data description or metadata (Hüner et al., 2011). A fact-oriented approach used in governance frameworks is grounded in natural-language and makes it easier for domain experts and line-of-business stakeholders to contribute (Leenheer et al., 2010). It is attribute free, accepts change and is flexible. Douglass et al. (1977) outline that user attitude in information systems generally reflects a psychological condition of their feeling towards the expansion or change of the system. Between stakeholders (users) and those in charge of system application - there must be a highly interactive relationship.

Additionally, Edmondson (2003) reports that if working closely with each other, in their sense-making process, individuals tend to develop shared assumptions - and share the way they interpret and apply new knowledge and experience. Such cognitive frames affect learning. The structure allows the leader to communicate mental models to the team members (Madhavan & Grover, 1998). Governance teams can be seen also as change-agents that therefore must initiate interaction with business stakeholders and users in order to create the proper involvement which can achieve user satisfaction as well (Amoako-Gyampah & White, 1993).

At last, the overview of claims provided by different authors listed in this section may generate hypothesis: It could be that *Governance Team Leadership (GTL) leads to an increase in Line-of-Business Stakeholders Participation (LOBSP).*

4.3.4. H6: GOVERNANCE TEAM LEADERSHIP (GTL) --> CROSS-FUNCTIONAL INTEGRATION (CFI)

Governance team leadership (GTL) integrates governance with change management and resistance to change with leadership theory. Data governance stewardship team members need to have two sources of the team leader's effectiveness: power/influence via emission of strong cross-functional team identity, and transformational leadership and behavior via communication and knowledge sharing. One of the data governance span's lower order constructs - cross-functional integration (CFI) - is built from a share of information and ideas between functions and cross-functional communication to resolve data issues.

A considerable number of researchers contributed to communication, knowledge sharing and the structure initiation dimension of governance team leadership in the setup of impact on governance span. Cordero et al. (1998) highlight that members of cross-functional teams generally work harder, are more involved in their jobs and face more pressure as they need to integrate different functional perspectives. This increases the amount of information shared proactively, and communication in data governance stewardship team and outside the team.

Communication, knowledge share and work and task scheduling efficiency of data stewardship teams could be deduced from Lawrence and Lorsch (1986), who support the creation of coordinating groups - cross-functional teams. They argue that these groups learn the language of all functions involved, and act as translators for others in their home functions. Teams decrease language barriers across functions as well as perceived conflict (Griffin, 1993). Kogut and Zander (1992) claim that the transfer of implicit knowledge still persists as a substantial challenge within organizations, particularly in cross-functional activities as knowledge is arranged and structured differently in the various functional units (Madhavan & Grover, 1998).

Within overall complex and always changing organizational structures, a span of governance is not being reduced if a proactive data stewardship governance team is communicating and sharing their knowledge gained from the fact that data governance provides the means for enterprise-wide oversight of roles and responsibilities for the data. The workload in a cross-functional team is larger and more complex compared to the one in functional activity. These factors affect the even quality of life of the employee. Therefore, the team is loaded with the most talented employees, with expectations that this call-in-service will reduce their risk of unemployment, advance their careers and increase their motivation. Such motivation of the data stewardship team, increases their proactivity, leadership, and productivity (Pimenta et al., 2016).

While there are many benefits of the cross-functional team, it requires much thought, work and planning to make it effective, due to initial challenges in communication between the team members and resistance to change (Wilemon & Cicero, 1970). Such initial challenges drive superior planning and communication skills of the data governance team, passed on in the way it communicates with operational data stakeholders. A successful member of a data governance team is a leader, with organizational and facilitation skills, who needs to drive scheduling and leading meetings, is used to collaborating with others and following up on issues (Plotkin, 2013).

Interdepartmental connectedness is defined as the extent to which formal and informal communication and contact is possible between individuals from different functional areas in the firm (Jaworski & Kohli, 1993). High outcome interdependence that comes from more and more frequent data governance iterations creates a cooperative frame of mind, leading to more data share, constructive approach to data issues. Leaders play a persuasive role in the application of knowledge by coaching and developing team members and managing the team dynamics (McDonough & Barczak, 1991) (Massey, Montoya-Weiss, & Brown, 2001) (Yukl, 2013). The work from Edmondson (2003) elaborates how characteristics of team leaders significantly affect the learning in teams through the application of acquired knowledge. Through a successful knowledge sharing-acquired learning approach to operational data stakeholders, data governance stewardship team members' leadership will increase the share of information, communication and joint work on data issues.

In comparison, the absence of task structure ruins the process where team members clearly understand their roles and responsibilities, which is the main obstacle to the success of cross-functional teams (Thamhain, 2007). In successful teams, leaders are able not only to passionately communicate vision but also to effectively outline to the team the process by which it should be accomplished (Sarin & McDermott, 2003). Cespedes (1993) suggests that structure initiation with planning process facilitates effective collaboration on implementation, on setting targets, and on activities incorporation into the overall objectives of the department or organization.

There are also authors that worked on the team identity dimension of governance team leadership with the idea of the impact on governance span. A cross-functional team is considered to recruit high-value roles giving to members of the team a positive professional image (Pimenta et al., 2016), contributing to team identity and its impact on gaining more followers across functions and increasing span. There are inherent biases and stereotypes that a functional line of the business unit holds against other units (Griffin & Hauser, 1996). From the theory of social identities by Ashforth and Mael (1989), functional identities produce these inter-functional biases and stereotypes. Consequently, it is difficult for members of cross-functional teams to increase the span of governance, information sharing and collaboration (Griffin & Hauser, 1996). Several studies have reported the advantages of overruling this by creating a solid sense of team superordinate identity. Sethi (2000) supports this method as it impacts individuals' previous group identities and enriches team effectiveness.

Operational data stakeholders follow strong governance team identity and advance in their activity above the previous average of their functional areas. Ford and Randolph (2016) and Pinto et al. (1993) suggest that teams, as well as managers in teams, are likely to focus more on organization-wide goals rather than on purely functional goals following the creation of a superordinate goal. This reduces latent conflict between functions that originally come from high differences in goal orientations. As a result, governance span is likely to increase across more functions.

High superordinate identity is generated by high autonomy given to team members while linking their responsibility, accountability, and evaluation of the cross-functional team (Ashforth & Mael, 1989). Data stewardship governance teams, whether they want it or not, end up with a high level of autonomy, as soon after their formation they will have a high rate of self-decided data policy, rules, and procedure. Their expertise simply positions them as the data authority to the whole organization. Lawler and Hall (1970) outline that the job situation is central to the person and his or her identity. Gurin et al. (1984), note that it affects individual self-esteem by creating a team identity. With proactively proving a positive relationship with each functional area, the data governance stewardship team functional manager unlocks easier resources from the functional manager (Simsarian Webber, 2002). Such processes emerge from a strong reputable team identity that leads to the climate of trust.

Eventually, according to the content postulated in this section, it can thus be suggested that *Governance Team Leadership (GTL) leads to an increase in Cross-Functional Integration (CFI).*

4.4. SECONDARY HYPOTHESIS

The hypotheses of this research are divided into two parts: primary hypotheses (marked with asterisk *) that primarily guided this research, and secondary hypotheses that are included due to the exploration-driven nature of this study. H1, H4, H7, H8, and H9 are secondary hypotheses covered in this section.

4.4.1. H1: CUSTOMER-CENTRIC ORIENTATION (CCO) --> DATA COMPLIANCE INNOVATION (DCI)

Customer-centric orientation (CCO) 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 (which includes revised financial metrics and leadership commitment). The innovation part of the concept of data compliance (DCI) is based on the integration of innovation and customer engagement (customer interaction orientation). This can be applied in the setup of data compliance with GDPR as an example, as regulation opens a new communication channel that can be used in innovative ways to add value to customer engagement and interaction.

A large and growing body of literature has investigated the relation between similar constructs to customer-centricity and innovation. Jaworski and Kohli (1993) identified that the collection, storage and analyzing 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 unrelated products and services, while the development of related ones is directly increased by inter-functional coordination. This is one of three customer-centric dimensions in this research named organizational integration.

The findings of this section, while preliminary, suggest that *Customer-Centric Orientation (CCO) leads to an increase in Data Compliance Innovation (DCI).* This relationship is already assumed and explained in more detail in the hypothesis where customer-centric orientation (CCO) mediates between data governance span (DGS) and data compliance innovation (DCI). It is listed as a secondary hypothesis in order to assess its strength.

4.4.2. H4: CUSTOMER-CENTRIC ORIENTATION (CCO) --> LINE-OF-BUSINESS STAKEHOLDERS PARTICIPATION (LOBSP)

Customer-centric orientation (CCO) consist 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 (which includes revised financial metrics and leadership commitment). Cross-functional integration (CFI) is a subconstruct of data governance and relates to the share of information and ideas between functions and cross-functional communication to resolve data issues. Line-of-business stakeholders' participation (LOBSP) is also a subconstruct of data governance and relates to the formal engagement which assumes stakeholder participation responsibility and formulation of objectives, evaluation of results and use of output.

Several authors expressed their thoughts on how customer-centric orientation (CCO) impacts line-of-business stakeholders' participation (LOBSP). Advanced interaction with a customer regarding matters of their data processing improves the span of data and adds more data (Ian Phau and Min Teah, Kim, & Kim, 2014). One of the major reasons to implement a data governance program is to enable better decision-making, lately renamed as business analytics. Several systems need to be connected and the quality of data is imperative to ensure the confidence that a decision-maker needs to have in the decision.

Very often customer-centric goals motivate line-of-business stakeholders to engage in the governance program. Smith (2008) outlines that one of the major targets of a customer-centric information integration concept is engaging line-of-business stakeholders as primary business owners for data in MDM initiatives. In customer and market facing units, knowledge sharing naturally increases successful collaboration as there is so much to learn from each other, in day-to-day practices of dealing with customers and consequent customers' reactions. In the research, organizations with a low level of learning between the sales and marketing functions were evidenced as the least collaborative (Loermans, 2002). Such a culture of collaboration increases line-of-business stakeholders' willingness to participate. Cespedes (1993) indicated that the development of structural linkages in customer-centric departments (e.g. project teams, task forces, job rotation, formal meetings) not only improves coordination, but also signals to the employees the importance placed on collaboration by senior management. A positive management attitude towards coordination of sales and marketing goals and activities will positively influence the drivers of collaboration. In a quantitative study, Maltz and Kohli (2000) concluded that the use of customer-centric organizational integration seems to be generally effective in reducing explicit conflicts between marketing and other functions.

4.4.2.1. MEDIATING ROLE OF CROSS-FUNCTIONAL INTEGRATION (CFI)

Several attempts have been made in the body of knowledge to rationalize the role of the cross-functional concept as a mediator with models that had some level of similarity. Having cross-functional teams and successful cross-functional span of governance - brings one collaborative assembly line for data reports, metrics, insights and decisions. It also creates innovative, proactive and engages business users with new ideas around data (Leenheer et al., 2010).

Jaworski and Kohli (1993) define market orientation as the organization-wide generation of market intelligence about future customer needs. Propagation of that intelligence across more departments will provide better results. Day (1994) argues that a market-driven culture needs to result in functionally coordinated action directed at gaining a competitive advantage.

Even the role of 'chief customer officer' as one of the major responsibilities has facilitation of cross-silo accountability, uniting departments in the development and understanding of the entire customer-centric strategy (Bliss, 2015). Client information is stored in various systems, while each system is controlled and maintained by different persons and different definitions for data quality (Lucas, 2010), and different attributes and notations. The same client is counted multiple times during the analytics process. The solution is in data governance program cross-functional span, based on allocating an appropriate single person in each domain to manage this different format of data (Niemi & Laine, 2016).

Cross-functional integration drives a higher rate of line-of-business participation due to higher trust in the system value. Data governance develops an additional tier of data explanations, above all department based, with application based sub-standards. This first common and holistic tier becomes relevant from a business context perspective (Leenheer et al., 2010).

Finally, statements of this section develop an idea that it is possible that *Cross-Functional Integration (CFI) mediates the relationship between Customer-Centric Orientation (CCO) and Line-of-Business Stakeholders Participation (LOBSP).*

4.4.3. H7 and H9: GOVERNANCE TEAM LEADERSHIP (GTL) --> PRIVACY PROJECT EFFICIENCY (PPE)

Governance team leadership (GTL) integrates governance with change management and resistance to change with leadership theory. Data governance stewardship team members need to have two sources of the team leader's effectiveness: power/influence via emission of strong cross-functional team identity, and transformational leadership and behavior via communication and knowledge sharing. Establishment accountability for customer privacy protection is one of the governance-driven projects that required efficiency (privacy project efficiency (PPE)). Accountability was distributed across operational data stakeholders in all functions, including line-of-business stakeholders. The project was led by the data governance stewardship team.

The relationship of leadership, communication and knowledge sharing is evidenced by a few authors under the context of project efficiency. Malach-Pines et al. (2009) evidenced a relationship of project characteristics with leaders' personality characteristics. Gundersen et al. (2012) suggest that transformational leadership was confirmed as having excessive applicability for project-oriented organizations. Effective internal formal communication (meetings and conferences), and informal communications (casual contacts) increases the level of coordination between different departments or their representatives. This has positive effects on their collaboration during the project, increasing project effectiveness (Le Meunier-FitzHugh & Piercy, 2007).

The enforcement of data governance policies is often confused with well-known management concepts of command and control. For a successful project completion, data governance really necessitates only an organizational culture that embodies collaboration, communication, knowledge sharing and leadership (Harris, 2011). Bryde (2003) notes that it is important that leadership drives the success of the project as a goal commitment of the team members is increased if the project's performance is connected with the team motivation. Durham et al. (1997) correspond that a leader is able to increase the motivation of the team members.

A data stewardship team already records and documents the rules and regulations around the data in their respective domains, and then communicates and shares among all stakeholders. This by default increases accountability and responsibility in the data regulations project, as it is no longer acceptable to provide violation justification with not having details of a particular rule or policy (Seiner, 2014). The same project manager gives the project the greatest chance of fast completion through the stability of leadership and management practices and continuity of knowledge management. Stability in project leadership is related with project speed, as there is no need for lost time for a project leader to get to know the team and the project again (Leana & Van Buren, 1999). A new perspective in leadership can cause a change in tactics and this may lengthen project schedules (Lynn & Akgun, 2012).

4.4.3.1. H9: MEDIATING ROLE OF CROSS-FUNCTIONAL INTEGRATION (CFI)

Cross-functional integration (CFI) is a subconstruct of data governance and it relates to the share of information and ideas between functions and cross-functional communication to resolve data issues.

Firms are progressively using cross-functional teams in projects (Daily & Huang, 2001). Cross-functional interactions increase levels of diverse knowledge, ideas, and expertise (Joseph Tidd & Bessant, 2013). This makes people aim to increase either their gain or their spread of knowledge (Robbins, 2003). Rajesh Sethi (2001) notes that cross-functional integration decreases the difference in values that exist in functional areas and information-sharing across the whole lifecycle of enterprise information systems implementation. Problems in projects are earlier identifiable and solutions earlier shared and agreed upon by all parties (Santa et al., 2011). Creativity and problem solving are improved with assembling the knowledge base from different units (Lampel, 2001). High levels of team problem-solving and quick trouble-shooting are positively related to faster project execution.

The team becomes an effective venue for defining and communicating function-specific requirements for project reporting and analytics. Such cross-functional requirements exchange density increases the effectiveness of identifying key performance indicators for the business, and key governance or data quality indicators. The group at any moment can review the proposed data insights or underlying conceptual model, give feedback on a report draft, or enrich it with additional key data sources required from their own domain knowledge. Regardless of the compliance project, the team can become a major channel of cross-functional agreements and decisions on business requirements (Krensky, 2014).

In the end, the rationalization provided in this section forms the basis for the possibility that there is the *mediating effect of Cross-Functional Integration (CFI) on Governance Teal Leadership (GTL) - Privacy Project Efficiency (PPE) relationship*.

4.4.3.2. H7: MEDIATING ROLE OF LINE-OF-BUSINESS STAKEHOLDERS PARTICIPATION (LOBSP)

Line-of-business stakeholders' participation (LOBSP) is also a subconstruct of data governance and relates to formal engagement which assumes stakeholder participation responsibility and formulation of objectives, evaluation of results and use of output.

A culture of accountability in data governance setup is based on necessary education-awareness of the data governance program and creating a deeper level of understanding of data related issues. An incentive mechanism to reward those who meet or exceed their performance targets is shown as a good strategy to develop responsibility.

Korhonen et al. (2013) suggest that this is therefore recommended in metrics in measuring the effectiveness of the data governance program where line-of-business stakeholder participation is required. A data governance program at first addresses accountability. To appoint line-of-business stakeholders and to give them the authority to implement, consolidate and manage all data governance efforts in their domain, while tying their project efficiency related performance directly to their incentives or compensation drives project efficiency (Korhonen et al., 2013). Collaboration is necessary for the knowledge flow; the leaders in a data governance stewardship team are the source and should have the willingness to share (Huber, 2001). However, for an eventual successful outcome, the target must value the new knowledge and have the capability to absorb it (Connell et al., 2003). Target refers to line-of-business stakeholders and their participation. This source-target mechanism directly impacts the effectiveness of inter-project learning as shown in the work of Landeata (2008).

These findings suggest that there may be *the mediating effect of Line-of-Business Stakeholders Participation (LOBSP) on the Governance Teal Leadership (GTL) - Privacy Project Efficiency (PPE) relationship.*

4.4.4. H8: MODERATING ROLE OF LINE-OF-BUSINESS STAKEHOLDERS PARTICIPATION (LOBSP)

Cross-functional integration (CFI) is a subconstruct of data governance and it relates to the share of information and ideas between functions and cross-functional communication to resolve data issues. Line-of-business stakeholders' participation (LOBSP) is also a subconstruct of data governance and relates to formal engagement which assumes stakeholder participation responsibility and formulation of objectives, evaluation of results and use of output. Establishment accountability for customer privacy protection is one of the governance-driven projects that required efficiency (privacy project efficiency (PPE)). Accountability was distributed across operational data stakeholders in all functions, including line-of-business stakeholders. The project was led by data governance stewardship team.

This concept of the impact of similar concepts to line-of-business stakeholders' participation has been rationalized in literature. Kagermann et al. (2011) argue that within compliance projects, legal provisions, cross-functional data exchange, and intra-company uniformed reporting require manipulation with clearly specified business objects (e.g. materials, customers, and suppliers) in order to utilize integrated, automated business processes. Usually, centrally organized corporate metadata managers reside within a central IT department and have these objects in a central repository. However, they are hardly able to meet all these demands and must be supported by key users from several business divisions who contribute expert knowledge (Hüner et al., 2011).

Business-IT cooperation is an essential attribute of data governance (Kooper et al., 2011). Mainga (2017) suggests that a new collaborative project culture is needed to support the joint resolution of issues and decision in data-driven regulations. Organizational practices for updating the data and creating new data entries have evolved differently in different business units (Silvola et al., 2011). Different business units developed their own distinct data management practices and processes. This is a challenge for any enterprise-wide compliance project. Apart from technical aspects, only additional changes in the organizational practices, disciplines, and responsibilities that drive engagement of line-of-business stakeholders and procedures will disturb this rigid structure.

Without mechanisms of authority formalization and control, failure is likely to happen. Ownerships, roles, and responsibilities of data governance provide a process and structure for managing information as a resource and require silo-break-down at its heart (Vilminko-Heikkinen & Pekkola, 2017). Increased efficiency around decisions of which data to processes and use in compliance projects comes from linking line-of-business data stakeholders with agreements about their clear roles and responsibilities, which is the product of data governance program.

Slack et al. (2010) argue that it is important to gain a better understanding of stakeholders' expectations in regards to the operational performance of the projects conducted because such understanding can enhance the final project efficiency. Business Process Management (BPM) literature is rich in its focus on this issue of lack of line-of-business stakeholders' involvement and understanding of the processes in projects. Evolving firms are usually designed over isolated functional silos, generally forgetting important connecting processes in such evolution. BPM as a concept implies monitoring and optimizing these silo-spanning business processes and utilizing a process-oriented approach to improve eventual performance (McCormack, 2007), in case of longer temporary or repeatable projects.

Major challenges in BPM adaptation arise due to the lack of collaboration between the organization's relevant BPM stakeholders. The tier of governance driven data explanations will be shared and used across units only if there is an organization-wide governance team which rigorously defines and monitors attributes that explain the data. However, only if there is proper participation of line-of-business stakeholders, will business objectives be discussed, shared and start to be formulated over time. Embedding them as policies within process control will be a start of secure governance (Leenheer et al., 2010).

Conclusively, a probable explanation that results from this section is that there is *the moderating effect of Line-of-Business Stakeholders Participation (LOBSP) on the Cross-Functional Integration (CFI) - Privacy Project Efficiency (PPE) relationship*.

5. RESEARCH METHOD

To establish awareness and relevance of the research problem, a literature search was first conducted. Based on Webster and Watson (2002) a literature review has been conducted in order to identify relevant literature on innovation, efficiency, governance, leadership, and customer-centricity. The research question was in the exploration phase for some time. There are more details on the exploration phase in the section related to constructing conceptualization. Looking into potential causal relations between different concepts from processed body-of-knowledge, over the time the integration of different concepts was used for selected for final variables: governance, vertical and horizontal integration with stakeholder theory; change management, resistance to change with leadership theory; customer-centricity concept with integration concept, innovation and market orientation with customer engagement; efficiency from project management with and accountability. Accountability was distributed across operational data stakeholders in all functions, including line-of-business stakeholders. The research question obtained its final form.

Following Hunter et al. (2016) the research is not intended to be classified as a scientometric study, and according to Leydesdorff (2016) as the purpose is not to present all papers dealing with all concepts of this study. However, the objective is to present a comprehensive overview of different understandings of observed variables by identifying research papers in the major journals of each discipline.

Identified databases and database centers 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, analysts companies, discussion groups, and professional organizations.

Identified were major publications, in the appropriate balance between the most recent and the most relevant ones.

Induction and deduction will be used together in research reasoning. Induction often when observing facts and performing root-cause analysis. Deduction when testing weather hypothesis is capable to explain the fact.

A quantitative method was selected with the online survey as a data collector. With qualitative research ethical treatment of participant was in risk due to a delegation of interviews and due to organizational sensitivity of data governance as a transformational project and due to its sensitivity due to its an aim-for-control and aim-for-compliance nature: project. In the theoretical background section, it was detailed that governance is about change that brings resistance. Listed were examples of challenges that will have to be faced in qualitative research in order to get rational answers that are not biased by underlying organizational politics. Used survey on the other side completely protected anonymity and minimized the risk of the mentioned bias. The major idea of the research is practical, with a focus on applied scientific nature and predictive study, exploratory rather than explanatory, self-correcting with built-in checks along the way, empirical (perceptions, beliefs, and attitudes carefully checked against objective reality), solving problems rather than just gaining knowledge, predicting effects and finding causes, developing interventions rather than theories. Quantitative research methods are used also as the aim was to provide a relatively conclusive answer to the research questions. The standardized, reputable methodology is supposed to provide the results trustworthily. With statistically significant sample sizes, the results can be generalized to an entire target group.

The survey is developed by balancing literature and fieldwork. The instrument was being developed with parallel consultation with subject matter experts with significant project experience, from academic and from professional consulting practice. Following one round of questionnaire pre-testing was conducted with 30 records collected, where some questions were revised. In the review of questions, the focus was to identify: ambiguous wording, double-barreled questions, loaded questions. The pilot test evaluated the Cronbach Alpha and Exploratory Factor Analysis. Five-point Likert-type scales were selected for measurement. Sample and sampling size were determined and data collection started.

Data analysis, processing, and hypotheses testing were performed with structural equation modeling (SEM) partial least square (PLS) statistical method using SmartPLS tool. More details are in the section on data analysis and results.

5.1. ANALYSIS PLAN - STRUCTURAL EQUATION MODELING AND PARTIAL LEAST SQUARE

Structural Equation Modeling (SEM) refers to a class of multivariate analysis techniques that combine the use of latent variables (LVs) with path analytic modeling, the use of factor analysis and regression analysis, - therefore referred to as second-generation multivariate analysis techniques (Fornell & Larcker, 1981b). The relationships between the theoretical constructs are represented by regression coefficients between the factors. It is not assumed that the latent factors completely explain the observed variation; each observed variable is associated with a residual error term. SEM aims to obtain estimates the factor loadings, the variances and covariances of the factor, and the residual error variances of the observed variables. Emphasis of measuring latent (unobservable) variables by multiple indicators combined with an econometric perspective of prediction through a directed graph of relationships give SEM popularity across many disciplines (W. Chin, 1998). Most critiques that have been raised against the use of SEM are around the issue of causal interpretation.

SEM fits with the purpose of this research as SEM path model reflects our thinking in chains of causal relationships and helps to translate such theories into data analysis. The real strength of SEM is, that we may specify and estimate more complicated path models, with intervening variables between the independent and dependent variables, and latent factor as well. The model specification is usually guided by a combination of theory and empirical results from previous research, and after the model is specified, it is possible to estimate factor loadings and (co)variances. It is possible also to conduct a statistical chi-square test to assess how well the hypothesized model fits the data.

The Partial Least Squares (PLS) method was chosen as an SEM technique for the study. Partial Least Square (PLS) indicates path models analysis particularly with indirectly measured variables (measured through other variables) (W. Chin, 1998; Hair, 1998, 2013b). Thus the acronym "PLS-SEM" is used here to refer to SEM employing PLS (Kock & Hadaya, 2018).

Due to its multidisciplinary nature, IS field become a reference for other fields (Baskerville & Myers, 2002).

To test the hypotheses, partial least squares (PLS) is used, as a suitable method for latent variable path analysis. It is distribution-free and due to its strengths in prediction its fits well with structural equation modeling (Fornell & Bookstein, 1982). In studies that are based on surveys often occurs that indicators or constructs are not normally distributed and PLS is strong enough to absorb the error terms of indicators in such cases. PLS offers accurate predication capability (Fornell & Larcker, 1981a). 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 (W. Chin, 1998). Item loadings, internal consistency and discriminant validity of the measurement model are effectively analyzed in PLS (Gefen, Straub, & Boudreau, 2000). The field of information systems (IS) is strongly associated with the use of the partial least squares (PLS) technique (W. Chin, 1998). Furthermore, PLS has been extensively used in IS and it was spread to other fields over the years.

This research is dedicated to theory exploration rather than confirmation. SEM generally divided into Variance-based SEM / PLS-SEM (e.g. SmartPLS) and Covariance-based SEM (e.g. AMOS which is an extension module from SPSS). Variance-based SEM e.g. SmartPLS can be used for exploratory research whereas Covariance-based SEM is meant for confirmatory research/analysis.

Covariance-based SEM is focused on covariance and explanation of items' relationships, is based on theory confirmation and requires already strong prior theory and established questionnaire, needs sizeable sample e.g. > = 300, only support metric data types, supports only reflective constructs, support constructs with three-items and above, requires addressing issue of missing values as well as multi-collinearity before analysis. Variance-based SEM is dedicated on theory exploration rather than confirmation and does not necessarily entails strong prior theories and established operationalizations, it supports small sample e.g. < 100, supports both metric and non-metric data types, both reflective and formative constructs, it does support constructs with single-item, supports data sets with missing values as well as data sets with multicollinearity. Compared to covariance-based methods. PLS distributional assumptions are more flexible, which in turn could result in more reliable findings (Gefen et al., 2000). In other words, no distributional assumptions are required for PLS which is advantageous during data analysis.

5.2. 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). However, scale adaptation was necessary to conduct. Many constructs can be conceptualized at different levels in a hierarchy, from general towards more specific. Very often, the reason for scale adaptation is a change of in this hierarchy and reassignment of different content areas to the construct. Consequently, the amount of items for that content area has to be added to the scale while some others have to be dropped. Multi-item scales are commonly refined based on item correlations while having such procedures not described precisely enough for an exact replication (Finn & Kayande, 1997). In order to find the best coefficient alpha for the dimension (Churchill, 1979) suggests that items substantially lower than others should be dropped and (Kopalle & Lehmann, 1997) show that eliminating such poor items positively impacts on reported alpha. As (Churchill, 1979) states set of items generated to capture a construct is often uncertain and exploratory factor analysis is used to eliminate items that fail to load strongly (F. Floyd & Widaman, 1995). (J. Anderson & Gerbing, 1988) show how confirmatory factor analysis can be used to identify the item most inconsistent with the measurement model and drop it in order model to fit.

As suggested by (Robinson, Shaver, & Wrightsman, 1991) the first step in scale construction was writing the items to be included in the scale. Initially, a number of items were created based on the literature review used to develop the conceptual definition. To cross-check the selection of items and to generate additional items, the mentioned group of experts were shown the definition of constructs and asked to generate scale items that they would use in the model. The resulting items were then reduced and refined through discussion between author and experts in order to select items most closely related to the definition of the construct and to eliminate closely related items.

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). In developing the measures, mentioned adaptation to the focal concepts of this research took place (Customer Centric Orientation (CCO), Data Governance Span (DGS), Line-of-Business Stakeholders Participation (LOBSP), Cross-Functional Integration (CFI), Privacy Project Efficiency (PPE), Governance Teal Leadership (GTL), Data Compliance Innovation (DCI)) while maintaining original concepts (Manager Involvement (Vanlommel & Brabander, 1975), Cross-Functional Integration (Enz & Lambert, 2015), Structure Initiation (Sarin & McDermott, 2003), Superordinate Identity (R. Sethi, 2000), Internal Integration (Swink & Schoenherr, 2015), Information Management (Dale L. Goodhue, Wybo et al., 1992), Customer Centricity (Marsh, 2010), Project Internal Efficiency ((J. Pinto & Mantel, 1990) and (M. Pinto et al., 1993)), Degree of Innovation (Sarin & McDermott, 2003) and Interaction Orientation - Interaction Response Capacity (Ramani & Kumar, 2008). It is argued that that constructs used in this research are special cases some other constructs and thus sharing many key behavioral characteristics with these overarching concepts, while at the same time having some element of 'newness'. The existing constructs were incorporated it the body of knowledge focal constructs and therefore of the various insights from the literature from both sides were integrated.

This study argues that LOBP is a special case of Manager Involvement, CFI special case of Cross-Functional Integration, PPE special case of Project Internal Efficiency as they share many key behavioral characteristics with these overarching concepts while having some elements unique to data governance span related business stakeholders participation and cross-functional integration as well as GDPR privacy accountability related internal project efficiency.

On the other hand, the work assumes that integration of subsets of constructs of Structure Initiation and Superordinate Identity can produce operationalization for GTL 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).

The measures on Interaction Orientation from Ramani and Kumar (2008) are adapted for DCI, where sub-construct measures for Interaction Response Capacity had four questions and for Customer Empowerment contains three questions. IN-1 is an integrative dimension made from one question in Interaction Response Capacity combined with one question in Customer Empowerment. Other questions were not applicable in the context of this research as they were too specific to the research in the field of marketing and are not easily generalized to the case with utilizing customer interaction in case of GDPR compliance.

The measures on Manager Involvement (Vanlommel & Brabander, 1975) are adapted for LOBSP, where the original operational definition of the conduct had three indicators, related to design, implementation, and follow-up. LOBSP1 is an integrative dimension made from the first two indicators of Manager Involvement, where the formulation of objectives reference is taken from the first and statement on the engagements to assume responsibility is taken from the second. LOBSP2 is a representation of the third indicator where the evaluation of results and control on the use of system outputs operationalizations are utilized. Other expressions from the original construct were not applicable in the context of this research.

The measures on Cross-Functional Integration (Enz & Lambert, 2015)are adapted for CFI, where original measure had five questions derived from the construct Effectiveness of Cross-Functional Relationships (Ellinger, 2000) which had additional had seven questions. The statement on team sharing resources, ideas, and information between functions are incorporated into CFI1 and expression where the team conducts cross-functional communication to anticipate and resolve operational problems formed CFI2. Other questions from the original construct were not applicable in the context of data governance span related to cross-functional integration.

The measure on Project Internal Efficiency (J. Pinto & Mantel, 1990) adapted for PPE, where the original measure had three questions. The time-related measure was used in this research while the other two, budget-related and outcome-related measures were not used as they did not fit with the research goal. This is how PPE1 was established.

To measure GTL, the relevant portions of two previously validated instrument were utilized. Adapted are two out of four items from the Structure Initiation - Process Structure construct (Sarin & McDermott, 2003) (items related to scheduling the work to be done, and maintaining definite standards of performance) and one out of five items of Structure Initiation - Goal Structure construct from the same instrument (item about letting the team know what is expected of them). All three resulted items were integrated into one and this formed GTL1. One out of five questions of the construct Superordinate identity (R. Sethi, 2000) is also adopted (an item about behaving like a unified team). This is how GTL2 was formed. The other questions were not relevant to the research of data stewards leadership.

To measure CCO, the relevant portions of one previously validated instrument were utilized as well as two operational definitions. Adapted are two out of five items from the Internal integration (Swink & Schoenherr, 2015) (items related to awareness of each other's responsibilities and having common prioritization of customers). CCO1 integrated them into one question. Definitions from (Wybo et al., 1992) and (Devece Carañana, Peris-Ortiz, & Rueda-Armengot, 2016) on data being condensed and synthesized to improve analysis in my firm were bases for CCO2. Customer centricity definitions from (Marsh, 2010) made CCO3 and in particular two of them are integrated, one related to strategies and processes constantly explored for ways to sustainably differentiate and provide better customer experience and one related to customer metrics.

For compliance utility and measuring intention that interaction with customers under GDPR requirements can be extended into an opportunity for innovation the measures on Interaction Orientation from (Ramani & Kumar, 2008) are adapted. These measures for Interaction Orientation- Interaction Response Capacity and for Degree of innovation (Sarin & McDermott, 2003) have both four questions. DCI1 was made as an integrated question, using from the first one the question related to aim to interact with the customer as much as possible in order to collect more data for innovation and from the second one the statement related to the conception of product-related innovations during the development of GDPR interaction channel with customers. The measures from two other sub-constructs were specific to the research in the field of marketing and are not easily generalized to the case by utilizing customer interaction in case of GDPR compliance. For example, the measures such are a belief in customer concept or customer value management are less applicable outside and marketing context.

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. Data governance experts from Oracle Corporation, IBM and Ph.D. program from the University of Economics in Prague contributed here in the survey design, checked the proposed survey and gave their feedback. This was followed by some modifications of some of the survey instrument questions without major changes in the design of the study procedures. Based on their feedbacks and validation questions from the original scales were changed, integrated, coupled or deleted. The next step was a pre-test of 30 participants in total to check the overall validation of the proposed model. In the review of questions, the focus was to identify: ambiguous wording, double-barreled questions, loaded questions. 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 (W. Chin, 1998) The reliability of the constructs (except Customer Centric Orientation and Data Stewardship Leadership) was confirmed (Thorndike, 1995). The Cronbach's alpha for Customer-Centric Orientation and Data Stewardship Leadership was very close to the minimum acceptable value of 0.7; thus, accomplishing a reliable construct via a larger sample of respondents was thought to be promising.

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 and 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).

5.2.1. GENERATING MEASURES

Table 1: Scale adjustment procedure

italic	[abc]	~~abc~~	**bold**	$\boxed{\text{table}}$
kept from original question or operational definition	term and words added to the original question or operational definition	terms not used from the original set of construct questions or operational definition	original construct name	the question used in research

Source: Author´s own processing

- **Manager Involvement** from (Vanlommel & Brabander, 1975)

Indicate the degree of manager [business user] involvement in [data governance framework] (Vanlommel and Brabander 1975)

- In design: *Formulation of objectives*, ~~Evaluation of economic feasibility, Evaluation of operational feasibility~~

- Implementation: ~~Decisions concerning personnel,~~ *Formal engagement to assume responsibility*, ~~Responsibility for introducing necessary organizational changes, Development and implementation of new procedures~~

- Follow up: ~~Control on economic results, Control on operational results, Reporting about the functioning of the system~~, *Evaluation of results, Control on use of system outputs*

Compared to other similar companies, in the data governance framework of the observed firm:
LOBSP1 - business stakeholder involvement is higher in the *formal engagement which assumes their responsibility* (identify data to be governed, rules, policies, follow-up)
LOBSP2 - business stakeholder involvement is higher in the *formulation of objectives, evaluation of results and use of outputs*

- **Cross-Functional Integration** [of data governance team] (Enz & Lambert, 2015) made the scale is based on (Ellinger, 2000)

~~We are encouraged to work together across functions in our supply chain*~~

- *Team share resources, ideas, and information between functions* ~~in our supply chain~~

~~- We informally work together as a team with our supply chain members~~

~~- We achieve goals collectively with our supply chain members~~

~~- Team adapts business processes together with other functions to develop strategies~~

~~- Effectiveness of cross-functional relationships(Ellinger 2000)~~

~~- Informally working together~~

~~- Sharing ideas, information, and/or resources~~

~~- Working together as a team~~

- *The team conducts [cross-functional communication] to anticipate and resolve operational problems [data issue]*

~~- Achieving goals collectively~~

~~- Developing a mutual understanding of responsibilities~~

~~- Making joint decisions about ways to improve overall cost efficiency~~

It the observed firm: CFI1 - Within the data governance framework there *is a share of information and ideas between functions* CFI2 - Data governance framework assumes *cross-functional communication to resolve data issues*

- **Structure Initiation** (Sarin & McDermott, 2003)

Structure initiation - process structure - the degree to which the [data governance team member] organizes and defines the activities of [data owners].

~~Our team leader encourages the use of uniform procedures.~~

~~Our team leader decides what shall be done and how it will be done~~.

- [data governance team members] *schedule the work to be done.*

- [data governance team members] *maintains definite standards of performance*.

~~- Our team leader asks the team members to follow standard rules and regulations.~~

Structure initiation - goal structure - the degree to which the team leader lets [data owners] know what is expected of them and makes his/her desires known to the group.

~~- Our team leader~~ *lets the team know what is expected of them*~~.~~

~~- Our team leader makes his/her attitudes clear to the team members.~~

- [data governance team members] ~~make sure that his/her part in the team is understood by [data owners]~~

- **Superordinate Identity** (R. Sethi, 2000)

- [data governance team members] ~~felt strong ties to the team~~.

- [data governance team members] *behaved like a unified team*.

~~- Members behaved like departmental representatives who were driven by their respective departmental agendas.~~

~~- Members were committed to common project objectives.~~

~~- Members valued their membership in the team.~~

~~- Members felt that they had a personal stake in the success of the team.~~

In the observed firm:

GTL1 - Data governance stewards *schedule work to be done*, organize, *clarify and defines the activities* of operational data stakeholders and *maintain definite standards of performance*.

GTL2 - Data governance stewards *behave like a unified team*.

- **Internal Integration** (Swink & Schoenherr, 2015)

The extent to which [customer centric] intra-firm functional teams (operations, logistics, sales, marketing, supply management) work together to accomplish [customer centric direction]. ~~supply chain planning and execution.~~

- Functional teams are *aware of each other's responsibilities*

- Functional teams *have a common prioritization of customers* ~~in case of supply shortages and how allocations will be made~~

~~- Operational and tactical information is regularly exchanged between functional teams~~

~~- Purchasing decisions are based on plans agreed upon by all functional teams~~

~~- All functional teams use common product roadmaps and other procedures to guide product launch performance metrics promote rational trade-offs among customer service and operational costs~~

- **Information Management - Processing Information**

The degree to which (customer) data can be *condensed* and *synthesized* to improve *analysis* in my firm (Dale L. Goodhue, Kirsch, Quillard, & Wybo, 1992) (Devece Carañana et al., 2016)

- **Customer Centricity** (Marsh, 2010)

~~- People who are in charge of the customer-centric initiative are on a high hierarchical level~~.

- There is an organizational mindset where *strategies and processes are constantly explored for ways to sustainably differentiate and provide better customer experience.*

- *Measured is the evolving nature of the customer-firm relationship over time*. ~~The basis of this recognition is an understanding of metrics, such are f.e. customer lifetime duration, customer lifetime value, customer lifetime profit and understanding of the drivers behind them.~~

In the observed firm: CCO1 – Customer focused functional teams (operations, sales, marketing, customer service) *work together, are aware of each other's responsibilities and also in prioritization of customers* CCO2 - Rate of *customer data being integrated, consolidated and used for analysis* is high CCO3- *Strategies and processes are explored for ways to differentiate and provide better customer experience while using customer metrics*

Project Internal Efficiency (J. Pinto & Mantel, 1990)

– [The accountability reconciliation and establishment across the enterprise - as a part of GDPR project] has/will come in *on schedule.*

~~- [The accountability reconciliation and establishment across the enterprise - as a part of GDPR project] has/will come in on budget.~~

~~- The project that has been developed works~~

In the observed firm: PPE1 - The GDPR related *project* of establishing accountability for the customer data across the enterprise was finished fast or compared to other similar companies

Degree of Innovation (Sarin & McDermott, 2003)

~~The degree of "newness" [established within new GDPR interaction channel with customers]~~

- *Product-related innovations [were concepted] during the development of [GDPR interaction channel with customers].*

~~- High-quality technical innovations were introduced during the development of this product.~~

~~- Compared to similar products developed by our competitors, our product will offer unique features/attributes/benefits to the customers.~~

~~- Our product introduces many completely new features for this class of products.~~

~~- Compared to similar products developed by our organization, our product will offer unique features.~~

Interaction Orientation - Interaction Response Capacity (Ramani & Kumar, 2008)

- This firm has systems in place that record each customer's transactions and [*is aiming to interact with the customer as much as possible in order to collect more data* for innovation]

~~- This firm can identify all transactions pertaining to each individual customer.~~

~~- This firm analyzes previous consumer transactions at the individual customer level to predict future transactions from that customer.~~

~~- In this firm, all customer interfaces possess transaction information on individual customers at all times.~~

DCI1 - GDPR channel starts to be used in innovative ways to add value to customer engagement and to act on customer behaviors in order to drive trust, loyalty and even new services

5.3. SAMPLE AND SAMPLE SIZE

Samples are carefully designed and chosen, in order results to be generalized. Generalization of the results is supported by the fact that GDPR regulation is harmonized law and does not vary across countries, as well 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 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, 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 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 round 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).

Sample size determines the significance of correlations in research models and greater data collection sample size provides a higher statistical power of the model, giving higher value to the coefficient of relationships (Goodhue, Lewis, & Thompson, 2012; Meyers, Gamst, & Guarino, 2013). Where there is no generally established rule for sample size requirement, the sample size required for the current research can be determined by two accepted rules. The "10-times rule" method is the most broadly used minimum sample size estimation method in PLS-SEM (Hair, Hult, Ringle, & Sarstedt, 2017). There are several deviations of this method, but the most regularly seen is based on the rule that the sample size should be greater than 10 times the maximum number of inner or outer model links directed at any latent variable in the model (Goodhue et al., 2012). The dependent construct with the most independent variables is knowledge Innovation Orientation (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 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 analyzed.

Kock and Hadaya (2018) offered two related methods and verified the accuracy of both. Based on mathematical equations, as alternatives for minimum sample size estimation in PLSSEM are proposed the inverse square root method and the gamma-exponential method.

Based on the proposed inverse square root method, the minimum sample size is estimated as the smallest positive integer that satisfies

$$\hat{N} > \left(\frac{2.486}{|\beta|_{min}}\right)^2.$$

Where bmin is the lowest recorded statistically significant value of the path coefficient value in the model.

Inverse square root method can be calculated in MATLAB with the function ceil((2.486/bmin)^2), where bmin is a variable that stores the value of $|\beta|$min or in excel with the function ROUNDUP((2.486/bmin)^2), where bmin is the name of a cell that stores the value of $|\beta|$min (Kock & Hadaya, 2018). The relationship that records the lowest statistically significant path coefficient value in the model is Governance Team Leadership (GTL) – Line-of-Business Stakeholders Participation (LOBSP) (0.279). Thus, 80 is the minimum required sample size according to ROUNDUP((2.486/0.287)^2). Mediator specific indirect effects and moderating path coefficients were not considered.

Using inverse square root method researchers can generate estimates that are both fairly precise and safe, with both normal and non-normal data. Estimates will always be somewhat larger than the true minimum sample sizes required, which decreases stricter demands on data collection (Kock & Hadaya, 2018). Each analysis generates various path coefficients. Each ratio between path coefficient (β) and standard error (S) associated with it. Path coefficient refers to an effect that exists at the population level – a "true" effect. The ratio between path coefficient (β) and standard error (S) increases with higher path coefficient and with larger sample size, increasing at the same time probability that this ratio β/S will exceed the critical T ratio., giving less chances that effect at the population level will be mistakenly rejected. In other words, the power of the test will increase (Kock, 2015).

5.4. DATA COLLECTION

Survey method is employed to collect data for analysis and empirically test the proposed model of this study. Techniques and instruments for collecting and analyzing data heavily impact knowledge building. Surveys are the usual approach for data collection and questionnaires are the most commonly used method of data collection in field research (Webster & Trevino, 1995). Whenever sample size requirements are met, surveys are useful in answering many questions regarding an event in the Management Information Systems area (Pinsonneault & Kraemer, 1993). When surveys are well-defined, there are expectations on valid and easily interpretable data (Pinsonneault & Kraemer, 1993). They are easy to administrate, allowing generalizability, predicting behavior instruments (Newsted, Huff, & Munro, 1998). This work employs an online survey to collect the required data for model validation including constructs items, demographics, and qualifying questions.

The survey was hosted using the SurveyMonkey online survey application (www.surveymonkey.com. The survey was divided into six parts. Demographic questions were gathered in the first part. Next, items regarding Data Stewardship Leadership, Data Governance Span, Customer-Centric Integration and then two GDPR related constructs, Project Efficiency, and Innovation Orientation. Each survey took 4 minutes to complete on average. 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 (Appendix 1) 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. Throughout the authors' previous professional engagements, there was already the network of the roles that fit the research criteria and this first group. This network was from different countries of Europe and from different industries so it exactly fitted sampling choices. They were contacted via email or via LinkedIn messages. The second group was recruited via LinkedIn, with 'join my network' invite with a short message on the survey recruitment aim. 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).

5.5. DATA ANALYSIS

This part of research method segment covers structural and measurement model validation and data analyses including the higher order construct explanation, common method variance, data screening, measurement model evaluation, multicollinearity, the explanatory power of the model, model fit, effect size results, and control variable results.

5.5.1. HIGHER ORDER CONSTRUCT

This research includes a hierarchical component model. Data Governance Span (DGS) is higher order construct consisting of two lower order constructs: Line-of-Business Stakeholders Participation (LOBSP) within Data Governance Span and Cross-Functional Integration (CFI) within Data Governance Span.

Hierarchical component models consist of higher-order constructs and lower order constructs. Main purposes for such models are: decreasing occurrence of structural relationships under analysis in Partial Least Squares, addressing collinearity among first-order latent constructs by using them to create more general second-order constructs, first-order constructs may formatively measure a second-order construct if formatively-modeled indicators for a first-order construct are collinear (Hair et al., 2017).

The assessment of the higher order construct is affected by the relationships between the higher order constructs and its lower order constructs rather than its indicator variables. While these relationships are mapped as path coefficients in a PLS-SEM analysis, from a modeling perspective, they correspond to loadings (in case of reflective-reflective and formative-reflective hierarchical component models) or weights (in case of reflective-formative or formative-formative hierarchical component models). This is how they need to be interpreted as such (Ringle, Sarstedt, & Straub, 2012).

Usually, repeated indicators approach is used in such hierarchical component models where the indicators of the first-order constructs are used as indicators for the second-order construct. Where also higher order construct must be measured reflectively and formatively by the lower order constructs.

In the repeated indicator approach the lower order construct will explain nearly all of the variance in the higher order construct (R2 will approach 1.0) and to resolve this - additional two-stage approach is recommended: (1) first the repeated indicator approach is used to get factor scores for the lower order construct, then (2) the lower order constructs factor scores are used as indicators for the higher order construct. In both stages, other latent variables with relationships to focal lower order constructs or higher order construct are included in the model also (Hair et al., 2017) (Wetzels, Odekerken-Schröder, & van Oppen, 2009).

Two steps bring two models, one model to study the antecedents of lower order constructs (LOBSP and CFI) while keeping the higher order construct with all lower order constructs, and another model to study the paths from higher order construct (DGS), which are hypotheses H2 and H3. These two models will be referred to in the research as the first stage model and second stage model.

5.5.2. COMMON METHOD VARIANCE

Common method variance implies to the variance that is attributed to the measurement method rather than the research model, constructs and relationships (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003) and it is evidenced as a potential threat to the validity of research results (Sharma, Yetton, & Crawford, 2009). It is advised that ensuring participants' anonymity could reduce the negative effect of CMV (Podsakoff et al., 2003) and the data collection procedure was in this research was designed in a way that respondents' anonymity was protected. There was no request for data that can identify the firm or respondent. An IP address is not tracked, neither whether or an invited target profile participated in the study.

However, additional valuation of the impacts of common method variance on the research findings is highly recommended (Chin, Thatcher, & Wright, 2012).

Kock and Lynn (2012) suggested the full collinearity test as a comprehensive procedure for the simultaneous assessment of both vertical and lateral collinearity. Using this procedure, variance inflation factors (VIFs) are generated for all latent variables in a model. If there is any of a VIF greater than 3.3 - this is implied as an indication of that a model may be contaminated by common method bias. Therefore, if all VIFs resulting from a full collinearity test are equal to or lower than 3.3, the model can be considered free of common method bias (Kock, 2015).

In SmartPLS there is an automated procedure of calculating PLS algorithm with factor weighting scheme, and then from the collinearity, statistics reading inner VIFs. (This has to be done with adjusting the model that all constructs are pointing to one single construct, and sequentially do the calculation for each construct).

Table 2: VIFs from adjusting the model that all constructs are pointing to one single construct, and calculation for each construct

	LOBSP	**CCO**	**PPE**	**DCI**	**GTL**	**CFI**
LOBSP		1.698	1.66	1.693	1.577	1.59
CCO	1.401		1.362	1.322	1.388	1.305
PPE	1.498	1.54		1.4	1.505	1.517
DCI	1.355	1.285	1.214		1.329	1.36
GTL	1.502	1.601	1.566	1.525		1.415
CFI	1.771	1.764	1.854	1.826	1.661	

Source: Author´s own processing

Given the above analyses, we can conclude that the surveys appeared to have the minimal possibility of common method variance.

5.5.3. DATA SCREENING

Survey responses were examined to assess if any participants who completed the survey in a careless manner to quickly finish the survey. For example, one could select 'neutral' for all the constructs question items; hence, making a biased set of responses. There was only case eliminated this way.

If there are outliers in normal distribution it only means that the normal probability distribution seems to be a (hopefully) sufficiently good approximation to the frequency distribution of data. If you no reason can find why outliers still appear then these values are to be kept in the analysis. Normality test in SmartPLs is via interpretation of Excess Kurtosis and Skewness. "Skewness assesses the extent to which a variable's distribution is symmetrical. If the distribution of responses for a variable stretches toward the right or left tail of the distribution, then the distribution is referred to as skewed. Kurtosis is a measure of whether the distribution is too peaked (a very narrow distribution with most of the responses in the center). (Hair et al., 2017). When both skewness and kurtosis are zero (a situation that researchers are very unlikely to ever encounter), the pattern of responses is considered a normal distribution. A general guideline for skewness is that if the number is greater than +1 or lower than –1, this is an indication of a substantially skewed distribution. For kurtosis, the general guideline is that if the number is greater than +1, the distribution is too peaked. Likewise, a kurtosis of less than –1 indicates a distribution that is too flat. Distributions exhibiting skewness and/or kurtosis that exceed these guidelines are considered nonnormal. (Hair et al., 2017). Only one value exceeded the threshold for Kurtosis (DC), therefore the additional test was necessary.

However, still, the test for univariate and multivariate outliers was conducted and no outliers were identified. In order to find univariate outliers, a z-test was conducted (Tabachnick & Fidell, 2000) and no case is identified to have z scores with extreme absolute values greater than the critical value of 3.29. Moreover, the data were examined for multivariate outliers using the Mahalanobis Distance approach (Meyers et al., 2013). The chi-square test is applied ($p<.001$, $df=4$, where 4 as the degree of freedom equals the number of independent variables) to all composite variables and there were no cases appeared to have chi-square statistics greater than the critical value of 26.125.

Table 3: Excess Kurtosis and Skewness

	No.	**Missing**	**Mean**	**Median**	**Min**	**Max**	**Standard Deviation**	**Excess Kurtosis**	**Skewness**
CCO	2	0	0	-0.08	-3.037	1.887	1	0.519	-0.458
CFI	3	0	0	0.378	-3.067	1.526	1	0.117	-0.774
DCI	4	0	0	0.904	-1.807	1.807	1	0.945	-0.04
DGS	5	0	0	0.36	-3.14	1.646	1	0.7	-0.915
GTL	6	0	0	0.201	-2.37	1.795	1	-0.56	-0.222
LOBSP	7	0	0	0.282	-2.468	1.374	1	0.026	-0.843
PPE	9	0	0	-0.087	-1.973	1.8	1	-0.584	-0.238

Source: Author´s own processing

5.5.4. MEASUREMENT MODEL EVALUATION

The measurement model conducted testing of individual item reliability (indicator reliability), construct reliability and construct validity. Indicator reliability was assessed via item loadings and corrected item-total correlations.

An item-total correlation test is performed to check if any item in the set of tests is inconsistent with the averaged behavior of the others, and thus can be discarded. (Churchill, 1979). There was no item-total correlation found with lower than 0.2 or 0.3 value, which signals that the related item does not correlate very well with the scale overall and, thus, it may be abandoned (Everitt & Skrondal, 2010).

In fact, when deciding to use PLS, researchers opt for a composite-based approach to structural equation modeling (SEM) that linearly combines indicators to form composite variables (Lohmöller, 1989b) which serve as proxies for the concepts under investigation (Rigdon, 2016). The biases occur when using (1) composite-based partial least squares path modeling to estimate common factor models, and (2) common factor-based covariance-based structural equation modeling to estimate composite models. The results show that the use of PLS is still preferable, regardless of bias, particularly when it is unknown whether the data's nature is a common factor- or composite-based (Ringle et al., 2012).

The factor-based estimation in tools like SPSS focuses on the construct, while PLS determines the scores from the model estimation of composites. The PLS path model does not use an additional context (i.e. other constructs) and, thus, the loadings are created only by the context of the one construct that items belong to. It is possible to create dummy construct with all indicators of the model and then create a second construct with the same indicators, contacts both construct with a path (the direction does not matter) and run the PLS algorithm in SmartPLS and get outer loadings identical to principal component analysis results in SPSS.

Table 4: Outer loadings from SmartPLS, Principal Component Analysis, and Item-Total-Loadings

	CCO	**CFI**	**DCI**	**DGS**	**GTL**	**LOBSP**	**Moderating Effect 1**	**PPE**	**Principal Component Analysis**	**Item-Total-Loadings**
LOBSP1				0.823					0.75	0.72
LOBSP1						0.927			0.75	0.72
LOBSP2				0.798						
LOBSP2						0.919			0.71	0.68
CC1	0.789								0.58	0.73
CC2	0.725								0.43	0.75
CC3	0.846								0.57	0.59
CFI *							1.355			
GTL1					0.895				0.61	0.66
GTL2					0.913				0.68	0.6
PPE1								1	0.65	0.49
DCI1			1						0.47	0.61
CFI1		0.932							0.77	0.66
CFI1				0.813						
CFI2		0.937							0.79	0.52
CFI2				0.843						

Source: Author´s own processing

Reliability is the accuracy in measurements when the measurements are repeated. Tests for reliability are internal consistency and composite reliability. Construct reliability was tested through three criteria: Cronbach's α, Composite Reliability (CR) or internal consistency reliability, and Average Variance Extracted (AVE). Cronbach's α for each factor is used to test internal consistency. The composite reliability estimates the extent to which a set of latent construct indicators share in their measurement of a construct, whilst the average variance extracted is the amount of common variance among latent construct indicator (Hair, 1998). Composite reliability is a measure of the overall reliability of a collection of heterogeneous but similar items.

Cronbach's α for each factor showed a value higher than 0.7. Additionally, CR and AVE values are higher than the suggested value of 0.7 and 0.5, respectively (W. Chin, 1998; Thorndike, 1995). Thus, sufficient construct reliability was demonstrated.

Table 5: Construct Reliability and Validity

	Cronbach's Alpha	**rho_A**	**Composite**	**Average Variance**
CCO	0.705	0.729	0.83	0.621
CFI	0.855	0.856	0.933	0.874
DCI	1	1	1	1
DGS	0.836	0.837	0.891	0.671
GTL	0.777	0.782	0.899	0.817
LOBSP	0.827	0.829	0.921	0.853
Moderating Effect	1	1	1	1
PPE	1	1	1	1

Source: Author´s own processing

At a high level, validity refers to the capability to measure the right concept. Tests for validity are convergent validity and discriminant validity. Convergent validity is measured with checking

Average Variance Extracted (AVE) > 0.5. As for discriminant validity, the shared variance between each construct is to be compared with their AVE, and as the former needs to be smaller than the latter.

All items passed the threshold value of 0.4 for item loadings (Hair, 2013a). Any value of item loadings is still acceptable until CR and AVE do not get affected (and especially if a number of items are not too high) (CR is .70 or near to .70 and AVE is 0.5 or near to 0.5).

The measurement model was tested in terms of validity with discriminant validity through Confirmatory Factor Analysis (CFA). A matrix of item-loading was constructed in order to conclude that each item loads on its latent construct stronger than other latent constructs (W. Chin, 1998).

Table 6: SmartPLS Cross Loadings in Discriminant Validity (Confirmatory Factor Analysis)

	CCO	**CFI**	**DCI**	**DGS**	**GTL**	**LOBSP**	**Moderating Effect 1**	**PPE**
LOBSP1	0.386	0.532	0.319	0.823	0.435	0.927	-0.403	0.447
LOBSP1	0.386	0.532	0.319	0.823	0.435	0.927	-0.403	0.447
LOBSP2	0.311	0.493	0.231	0.798	0.494	0.919	-0.31	0.376
LOBSP2	0.311	0.493	0.231	0.798	0.494	0.919	-0.31	0.376
CC1	0.789	0.396	0.326	0.438	0.243	0.376	-0.234	0.297
CC2	0.725	0.262	0.193	0.232	0.159	0.146	-0.026	0.257
CC3	0.846	0.378	0.338	0.392	0.205	0.313	-0.15	0.269
CFI * LOBSP	-0.196	-0.438	-0.143	-0.468	-0.18	-0.387	1	-0.075
GTL1	0.188	0.506	0.034	0.531	0.895	0.429	-0.181	0.277
GTL2	0.285	0.489	0.167	0.548	0.913	0.477	-0.146	0.394
PPE1	0.349	0.436	0.435	0.5	0.374	0.446	-0.075	1
DCI1	0.378	0.28	1	0.328	0.115	0.299	-0.143	0.435
CFI1	0.394	0.932	0.261	0.813	0.54	0.494	-0.365	0.399
CFI1	0.394	0.932	0.261	0.813	0.54	0.494	-0.365	0.399
CFI2	0.449	0.937	0.264	0.843	0.489	0.543	-0.452	0.417
CFI2	0.449	0.937	0.264	0.843	0.489	0.543	-0.452	0.417

Source: Author´s own processing

A latent variable correlation matrix was created in which the diagonal line represents the square root of AVE values (Fornell & Larcker, 1981b) (Fortner-Larcker criterion in SmartPLS). These values are greater than each correlation value on the associated row and column (W. Chin, 1998).

Table 7: Fortner-Larcker criterion in SmartPLS – Stage one model

	CCO	**CFI**	**DCI**	**DGS**	**GTL**	**LOBSP**	**Moderating Effect 1**	**PPE**
CCO	0.788							
CFI	0.452	0.935						
DCI	0.378	0.28	1					
DGS	0.471	0.886	0.328	0.819				
GTL	0.264	0.55	0.115	0.597	0.904			
LOBSP	0.378	0.555	0.299	0.878	0.503	0.923		
Moderating Effect 1	-0.196	-0.438	-0.143	-0.468	-0.18	-0.387	1	
PPE	0.349	0.436	0.435	0.5	0.374	0.446	-0.075	1

Source: Author´s own processing

Table 8: Fortner-Larcker criterion in SmartPLS – Stage two model

	DCI	DGS	CCO	PPE
DCI	1			
DGS	0.328	1		
CCO	0.378	0.471	1	
PPE	0.435	0.500	0.348	1

Source: Author´s own processing

5.5.5. MULTICOLLINEARITY

The data set was investigated for multicollinearity. When two exogenous (independent) variables are strongly correlated, there is a high probability that they measure similar things; thus, collinearity exists (Meyers et al., 2013).

Two approaches are conducted to identify multicollinearity. First, test through a correlation matrix between the variables is performed (Fortner-Larcker criterion in SmartPLS), and all the values are below the suggested critical value of 0.8 except those in the relationship between lower-order and higher-order constructs (Tabachnick & Fidell, 2000), indicating no multicollinearity between the variables.

Table 9: Correlation matrix

	CCO	CFI	DCI	DGS	GTL	LOBSP	Moderating Effect 1	PPE
CCO	1	0.452	0.378	0.471	0.264	0.378	-0.196	0.349
CFI	0.452	1	0.28	0.886	0.55	0.555	-0.438	0.436
DCI	0.378	0.28	1	0.328	0.115	0.299	-0.143	0.435
DGS	0.471	0.886	0.328	1	0.597	0.878	-0.468	0.5
GTL	0.264	0.55	0.115	0.597	1	0.503	-0.18	0.374
LOBSP	0.378	0.555	0.299	0.878	0.503	1	-0.387	0.446
Moderating Effect 1	-0.196	-0.438	-0.143	-0.468	-0.18	-0.387	1	-0.075
PPE	0.349	0.436	0.435	0.5	0.374	0.446	-0.075	1

Source: Author´s own processing

The Variance Inflation Factor (VIF) was calculated for all the independent variables of the study. Multicollinearity exists when two or more independent variables are highly intercorrelated, increases standard errors, marks significance tests of independent variables unreliable, and stops the researcher from assessing the relative importance of one independent variable compared to another. Problematic multicollinearity may exist when the variance inflation factor (VIF) coefficient is higher than 4.0. (Kock, 2015)(Hair, 2013b).

If there are only reflective measures, then reporting only the inner model VIFs is sufficient. If there are also formative measures, there is a need to assess the VIFs of the indicators of the formative measures (outer model). In a reflective measurement model, multicollinearity is not an issue, as the latent variable is modeled as a single predictor of the values of each of the indicator variables, which are dependent variables. SmartPLS reports VIF for each predictor in a regression, all indicators in the outer model and for all constructs in the inner model (Hair, 2013b).

Table 10: Inner model

	CCO	CFI	DCI	DGS	GTL	LOBSP	PPE
CCO		1.075	1			1.257	
CFI				1.446		1.676	1.878
DCI							
DGS							
GTL		1.075				1.434	1.592
LOBSP				1.446			1.657
Moderating Effect 1							1.312
PPE							

Source: Author´s own processing

Table 11: Outer model

	VIF
LOBSP1	2.205
LOBSP1	1.992
LOBSP2	2.073
LOBSP2	1.992
CC1	1.217
CC2	1.568
CC3	1.685
CFI * LOBSP	1
GTL1	1.677
GTL2	1.677
PPE1	1
DCI1	1
CFI1	2.264
CFI1	2.326
CFI2	2.264
CFI2	2.506

Source: Author´s own processing

5.5.6. EXPLANATORY POWER OF THE MODEL

The range of R2 is in between 0 and 1, the higher level, the higher predictive accuracy. According to (W. Chin, 1998) and (Henseler, Hubona, & Ray, 2016). The R2 value of 0.67, 0.33, and 0.19 are considered strong, moderate, and week, respectively. Thus, the model demonstrated strong explanatory power. (J. Cohen, 1988) also suggests R2 values of .02, .13, and .26 as a weak, medium, and strong.

The explanatory power of the model was evaluated via the coefficient of determination or R-squared. The acceptable R^2 values of 0.403, 0.143, 0.383, 0.288 in the first stage model and 0.172 and 0.222 in the second stage model indicate sufficient amount of variance in the construct that captured verses amount was left unaccounted by the independent variables(1- R^2).

According to (W. Chin, 1998) R-square analysis provides an indication of model fit. There is a number of factors involved, that may indicate that there is something else that is accounting for the total variance in the dependent variable that is explained by the independent variable, such as a mediating variable. This might be an approximate value that researchers are able to explain in this field, one of the attempts to test this might be to narrow down the focus of the research, for example, look into its reflection only in one vertical considering other elements that impact that vertical.

Table 12: R Square and R Square Adjusted in the first stage model

	R Square	R Square Adjusted
CFI	0.403	0.391
DCI	0.143	0.134
DGS	1	1
LOBSP	0.383	0.363
PPE	0.288	0.257

Source: Author´s own processing

Table 13: R Square and R Square Adjusted in the second stage model

	R Square	R Square Adjusted
DCI	0.172	0.154
CCO	0.222	0.213
PPE	0.250	0.242

Source: Author´s own processing

5.5.7. MODEL FIT

If the model does not fit the data, the data contains more information than the model conveys. The obtained estimates may be meaningless, and the conclusions drawn from them become questionable. The global model fit can be assessed by means of inference statistics - tests of model fit, or through the use of fit indices -an assessment of approximate model fit. Model fit indices enable judging how well a hypothesized model structure fits the empirical data and, thus, help to identify model misspecifications.

The goodness of fit (GoF) has been developed as an overall measure of model fit for PLS-SEM. However, as the GoF cannot reliably distinguish valid from invalid models and since its applicability is limited to certain model setups, researchers should avoid its use as a goodness of fit measure. While a global goodness-of-fit measure for PLS-SEM has been proposed (Tenenhaus, Vinzi, Chatelin, & Lauro, 2005), research shows that the measure is unsuitable for identifying misspecified models (Henseler et al., 2016). Therefore, 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) (W. Chin, 1998). Although being applied widely in the area of IS (Tenenhaus et al., 2005), the GoF index has been criticized for its lack of power to validate models (Hair et al., 2017). Thus, SmartPLS provide them, they are at a very early stage of research and not fully understood. Apart from these developments, it is an open question of whether fit measured adds any value to PLS-SEM analyses in general. In fact, their use can even be harmful as researchers may be tempted to sacrifice predictive power to achieve better "fit".

(Henseler et al., 2016) explain in detail that the so global goodness of fit (GoF) for PLS by Tenenhaus et al. (2004) does not represent a fit measure and should not be used as such. However, they also show that the GoF may be useful for a PLS multi-group analysis (PLS-MGA) when researchers compare the PLS-SEM results of different data groups for the same PLS path model.

Unlike Covariance Based-SEM, PLS-SEM does not optimize a unique global scalar function. The term fit has different meanings in the contexts Covariance Based-SEM compared to PLS-SEM.

Fit statistics for CB-SEM are derived from the discrepancy between the empirical and the model-implied (theoretical) covariance matrix, whereas PLS-SEM focuses on the discrepancy between the observed (in the case of manifest variables) or approximated (in the case of latent variables) values of the dependent variables and the values predicted by the model in question (Hair et al., 2017).

(Ringle et al., 2012) 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 models (Esposito Vinzi, Wynne Chin, Henseler, & Wang, 2010). 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 (Ringle et al., 2012), the *Q^2* value resulted in a good model fit (predictive relevance) of 0.175>0 (Esposito Vinzi et al., 2010).

Predictive relevance Q2 and q2 (e.g., use blindfolding; Q2 > 0 is indicative of predictive relevance; q2: 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 14: Predictive Relevance Q2

	SSO	**SSE**	**Q^2 (=1-SSE/SSO)**
LOBSP	196	137.857	0.297
CCO	294	294	
DGS	392	147.299	0.624
PPE	98	73.468	0.25
GTL	196	196	
CFI	196	132.094	0.326
Moderating effect	98	98	

Source: Author´s own processing

The standardized root mean square residual (SRMR) based on transforming both the sample covariance matrix and the predicted covariance matrix into correlation matrices - is defined as the difference between the observed correlation and the model implied correlation matrix. Thus, it allows assessing the average magnitude of the discrepancies between observed and expected correlations as an absolute measure of (model) fit criterion. A value of less than 0.10 is considered a good fit. Henseler (2016) explains SRMR as a goodness of fit measure for PLS-SEM. This model has 0.104 and can be marginally accepted.

Normed Fit Index or NFI computes the Chi² value of the proposed model and compares it against a meaningful benchmark (Bentler & Bonett, 1980). The NFI is then defined as 1 minus the Chi² value of the proposed model divided by the Chi² values of the null model. Consequently, the NFI results in values between 0 and 1. The closer the NFI to 1, the better the fit. NFI values above 0.9 usually represent more acceptable fit. Lohmoller (1989a) provides detailed information on the NFI computation of PLS path models.

The exact model fit tests the statistical (bootstrap-based) inference of the discrepancy between the empirical covariance matrix and the covariance matrix implied by the composite factor model. As defined by (Dijkstra & Jörg Henseler, 2015) d_LS (the squared Euclidean distance) and d_G (the geodesic distance) represent two different ways to compute this discrepancy. The bootstrap routine provides the confidence intervals of these discrepancy values. 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".

PLS path modeling's tests of model fit rely on the bootstrap to determine the likelihood of obtaining a discrepancy between the empirical and the model-implied correlation matrix that is as high as the one obtained for the sample at hand if the hypothesized model was indeed correct (Dijkstra & Jörg Henseler, 2015). Bootstrap samples are drawn from modified sample data. This modification entails an orthogonalization of all variables and a subsequent imposition of the model-implied correlation matrix. In covariance-based SEM, this approach is known as 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.

In order to have some frame of reference, it has become customary to determine the model fit both for the estimated model and for the saturated model. Saturation refers to the structural model, which means that in the saturated model all constructs correlate freely.

Another promising approximate model fit criterion is the root mean square error correlation (RMStheta) (Lohmöller, 1989a). A recent simulation study (Henseler et al., 2014) provides evidence that the RMStheta can indeed distinguish well-specified from ill-specified models. However, thresholds for the RMStheta are yet to be determined, and PLS software still needs to implement this approximate model fit criterion. Note that early suggestions for PLS-based GoF measures such as the "goodness-of-fit" (see Tenenhaus et al., 2004) or the "relative goodness-of-fit" (Esposito Vinzi et al., 2010) are – in opposite to what their name might suggest – not informative about the goodness of model fit (Henseler, Ringle, & Sinkovics, 2009). Consequently, there is no reason to evaluate and report them if the analyst's aim is to test or to compare models.

Table 15: Model fit results from SmartPLS

-	**Saturated Model**	**Estimated Model**
SRMR	0.104	0.115
d_ULS	1.299	1.582
d_G	n/a	n/a
Chi-Square	infinite	infinite
NFI	n/a	n/a

Source: Author´s own processing

Table 16: rms Theta result from SmartPLS

rms Theta	**0.281**

Source: Author´s own processing

5.5.8. EFFECT SIZE RESULTS

Effect size is another criterion to assess the strength of a model. It reflects the statistical power of the relationships in the population (Hair, 2013b). According to (J. Cohen, 1988), $0.02<f^2\leq0.15$, $0.15<f^2\leq0.35$, and $f^2>0.35$ are considered small, medium, and large, respectively. Calculating the f^2

values, it was concluded that while identification and commenting perceived usefulness had large effect sizes, engagement and bookmarking perceived usefulness had medium effect sizes and reputation and enjoyment of helping others had small effect sizes. There is no single relationship with a value of less than 0.02.

Table 17: F Square

	CCO	CFI	DCI	DGS	GTL	LOBSP	PPE
CCO		0.169	0.167			0.031	
CFI				62,494.83		0.107	0.067
DCI							
DGS							
GTL		0.334				0.088	0.007
LOBSP				58,469.56			0.082
Moderating Effect 1							0.04
PPE							

Source: Author´s own processing

Table 18: F Square

	DCI	DGS	CCO	PPE
DCI	0.035		0.285	0.334
DGS	0.078			
CCO				
PPE				

Source: Author´s own processing

5.5.9. CONTROL VARIABLES RESULTS

There are two control variables used in this research. To fully understand the statistical population characteristics, location (European Union region) and industry details were gathered.

Effect size analysis using SmartPLS was applied to interpret the potential roles of control variables. To understand the effects of region and industry control variables, 12 dummy variables are created where cases were coded as 1 if it was the presence of particular region or industry or were coded as 0 if it was absence.

To analyze the impact of the aforementioned control variables on the dependent variables, a controlled model was run for each of the control variables separately. Next, the added control variable was linked to all the variables in the model. The R^2 value of the dependent construct was noted for each of the controlled models. The R^2 value of the endogenous construct in the default model was compared to the R^2 value of the same construct in the controlled model. According to (J. Cohen, 1988), the effect sizes of 0.02, 0.15, and 0.35 are small, medium, and large, respectively. All the effect sizes are considered to be small.

To categorize region, countries were grouped into five categories: North Europe (NE), West Europe (WE), South Europe (SE), Central Europe (CE) and Outside of European Union (OEU). Abbreviation used for industries: Financial Services (FS), Telecommunications (TC), Aerospace or Transportation (AT), E-Commerce or Retail, (ER) Technology, Software or Internet (TSI), Consulting (CO), Healthcare (HC), Other (OT).

There is a notifiable small effect of effect HC of 0.124 on CCO, 0.11 on PPE, TC effect on LOBSP of 0.108 and HC effect on PPE of 0.11 and TC on GTL of -0.145. There is only medium effect of HC on DCI of -0.228.

Table 19: F Squared from dummy variables to other variables in the model

	CCO	CFI	DCI	DGS	GTL	LOBSP	PPE
SE	0	0.046	0.001	0.008	0.001	0	0
WE	0.008	0.049	0	0	0	0.013	0
CE	0.004	0.003	0.002	0.004	0.002	0	0.003
OEU	0.002	0	0	0.003	0.011	0.031	0.002
FSI	0.007	0.009	0.002	0.001	0.003	0	0.006
OT	0.027	0	0	0.003	0.046	0.009	0.001
TC	-0.052	0.049	0.02	0	-0.145	0.108	-0.094
ER	0	0.002	0.011	0.002	0.008	0.012	0.019
HC	0.124	-0.228	-0.141	0	0.006	0.066	0.11
CO	0.021	0.003	0.006	0.002	0.02	0.01	0.01
TSI	0	0.001	0.014	0.027	0	0.03	0

Source: Author´s own processing

6. RESULTS AND DISCUSSION

This segment of the dissertation covers results and discussion through three subsequent parts. The discussion is integrated with the sections covering results related to the demographics of respondents, descriptive statistics and hypotheses testing.

6.1. DEMOGRAPHICS OF RESPONDENTS RESULTS AND DISCUSSION

Two demographic questions were asked by the participants. In total, 50% from financial services Industry, as the existence of data governance is associated with this highly regulated industry. Naturally, two other regulated industries, telecommunications, and healthcare follow with 8.2% and 10.2%. With regards to the region, 50% of participants were from Western Europe, followed by 21.4% from Southern Europe and 20.4% from Central Europe. This is also expected, considering maturity levels of IT infrastructure and IT spendings that influence the maturity of data governance software, and then associated frameworks. This is also expected considering that the United Kingdom was part of Western European stratum. There were no responses completed responses from Northern Europe, although it was ensured that it had proper representation in stratified sampling. There were 5 responses which were not completed from this region. In the overall comparisons of the stratums, it was recorded lower representation of target profiles and target companies in Northern European region which is indeed significantly smaller than Central, Southern and West European in terms of population and potential customer and party records that are processed by firms, indicating lower rate of occurrence of proper data governance teams and roles.

The percentages in the sample sizes per regions and industry are consistent with population stratum size results when breaking down per regions and industry all target roles (around 2000).

Below are listed some of the findings. This research does not aim to discuss in details obtained demographics findings and suggests that for in further research section.

Abbreviation used for industries: Financial Services (FS), Telecommunications (TC), Aerospace or Transportation (AT), E-Commerce or Retail, (ER) Technology, Software or Internet (TSI), Consulting (CO), Healthcare (HC), Other (OT). These industries cover business-to-consumer areas. Abbreviation in charts. EF1 stands for PPE1, IN1 stands for DCI1, DS1 and 2 stand for GTL1 and 2, BS1 and 2 stand for LOBSP 1 and 2, XF 1 and 2 stand for CFI1 and 2

AT scored the highest across all variables apart of DCI1. Aerospace or Transportation (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 governance frameworks as extensively as their customers.

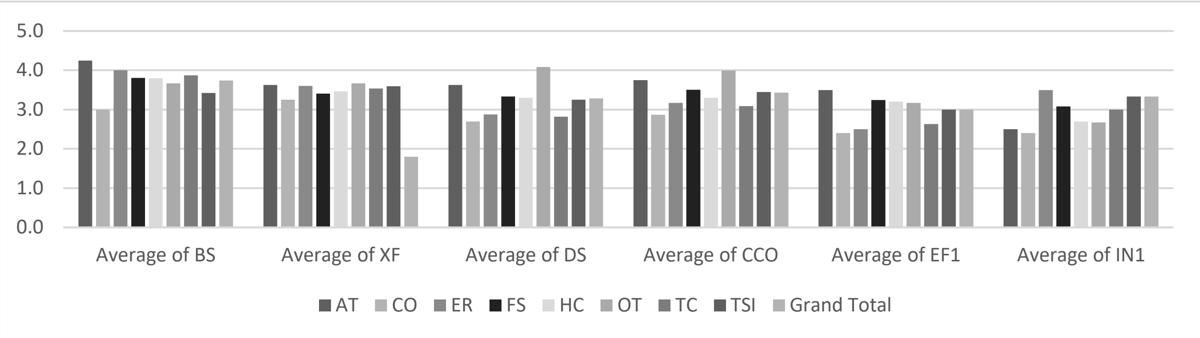
ER the second highest on BS, and XF and highest on DCI1. Third lowest on DS and second lowest on PPE1. E-Commerce and Retail are highly focused on innovation in data regulation (3.50

compared to all-industries-average of 3.00) and extensively uses data governance span, but does not obtain same results in project efficiency (2.50 compared to all-regions-average of 3.09).

TSI second lowest on BS. Technology, Software or Internet companies do not involve line-of-business stakeholders in governance frameworks, especially in the formulation of objectives, evaluation of results and use of outputs (LOBSP2 is 3.17 compared to all-industries-average of 3.66).

TC second lowest on DS and PPE1. The telecommunication industry is not using governance team leadership and was having lower efficiency in data compliance project (2.40 compared to all-industries-average of 3.09).

Chart 1: Industries



Source: Author´s own processing

Table 20: Industry distribution

	Count	Percentage
AT	4	4.1%
CO	5	5.1%
ER	4	4.1%
FS	49	50.0%
HC	10	10.2%
OT	6	6.1%
TC	8	8.2%
TSI	12	12.2%
Grand Total	98	100.0%

Source: Author´s own processing

Table 21: Means of industries

Row Labels	Average of LOBSP1	Average of LOBSP2	Average of CFI1	Average of CFI2	Average of GTL1	Average of GTL2	Average of CC1	Average of CC2	Average of CC3	Average of PPE1	Average of DCI1
AT	4.25	4.25	4.25	4.00	4.00	3.25	3.50	3.50	3.50	3.50	2.50
CO	3.00	3.00	3.00	3.20	2.80	2.60	2.80	3.20	3.00	2.40	2.40
ER	4.00	4.00	3.50	3.75	3.00	2.75	3.25	3.25	3.75	2.50	3.50
FS	3.90	3.71	3.71	3.84	3.49	3.18	3.43	3.55	3.63	3.24	3.08
HC	3.70	3.90	3.10	3.30	3.40	3.20	4.00	3.60	3.60	3.20	2.70
OT	3.67	3.67	3.83	3.83	4.33	3.83	2.67	3.83	2.83	3.17	2.67
TC	4.00	3.75	3.50	3.63	2.88	2.75	3.38	3.38	3.25	2.63	3.00
TSI	3.67	3.17	3.58	3.83	3.42	3.08	3.42	3.50	3.58	3.00	3.33
AL	3.82	3.66	3.60	3.73	3.44	3.13	3.40	3.52	3.51	3.09	3.00

Source: Author´s own processing

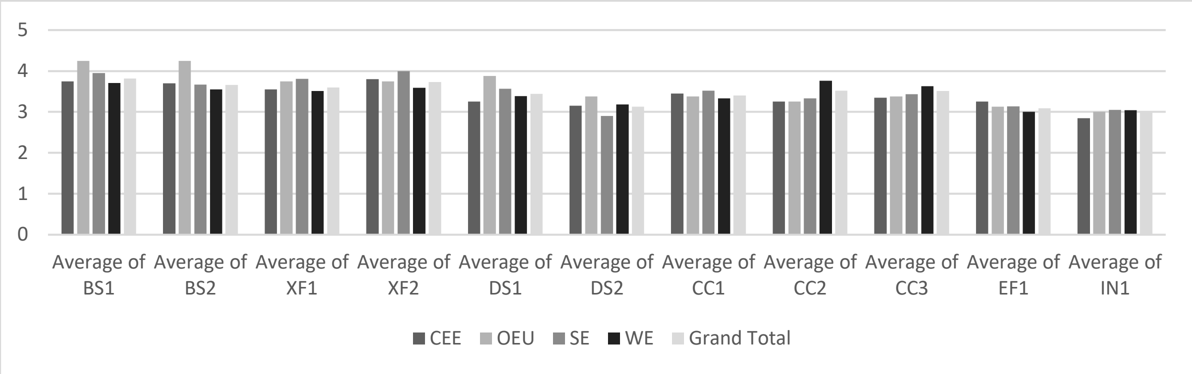
Abbreviations used: Central and Eastern Europe (CEE), Western Europe (WE), Southern Europe (SE).

Firms in Central and Eastern Europe (CEE) did not use innovation enough in data compliance and have the lowest leadership of data governance teams, especially in communication, knowledge transfer and work schedule. GTL1 and DCI1 were 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). LOBSP1 and GTL2 were the second lowest in CEE compared to all-regions-average (3.75 and 3.15 respectively). Average of GTL1+GTL2 scored the lowest in CEE, as well as DCI1, where former showed more shows more severe difference.

Southern Europe (SE) firms have highest cross-functional integration and horizontal data governance span, however, their governance team does not have an identity as much as in other regions, so high span must be obtained with communication, knowledge transfer and work-scheduling. GTL2 scored the lowest, both CFI1 and CFI2 the highest.

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 lowest, having both cross-functional integration and line-of-business stakeholders participation lowest compared to others. LOBSP1 and LOBSP2 scored the lowest, CFI1 and CFI2 scored the lowest, CC2 and CC3 the highest.

Chart 2: Regions



Source: Author´s own processing

Table 22: Region distribution

	Count	**Percentage**
CEE	20	20.4%
OEU	8	8.2%
SE	21	21.4%
WE	49	50.0%
Grand Total	98	100.0%

Source: Author´s own processing

Table 23: Means of regions

	Average of LOBSP1	**Average of LOBSP2**	**Average of CFI1**	**Average of CFI2**	**Average of GTL1**	**Average of GTL2**	**Average of CC1**	**Average of CC2**	**Average of CC3**	**Average of PPE1**	**Average of DCI1**
CEE	3.75	3.70	3.55	3.80	3.25	3.15	3.45	3.25	3.35	3.25	2.85
OEU	4.25	4.25	3.75	3.75	3.88	3.38	3.38	3.25	3.38	3.13	3.00
SE	3.95	3.67	3.81	4.00	3.57	2.90	3.52	3.33	3.43	3.14	3.05
WE	3.71	3.55	3.51	3.59	3.39	3.18	3.33	3.76	3.63	3.00	3.04
ALL	3.82	3.66	3.60	3.73	3.44	3.13	3.40	3.52	3.51	3.09	3.00

Source: Author´s own processing

6.2. DESCRIPTIVE STATISTICS RESULTS AND DISCUSSION

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. Although the PLS analysis method does not require normal distribution for data, skewness, and kurtosis measures are also provided. Accordingly, the distributions vary from right to left skewness. In terms of kurtosis, all the values are less than three which means the items have data with Platykurtic distributions. In other words, the values are wider spread around the mean.

Table 24: Descriptive Statistic Results

	No	Missin	Mea	Media	Mi	Ma	Standard	Excess	Skewnes
LOBSP	13	0	3.816	4	1	5	0.983	0.317	-0.864
LOBSP	14	0	3.663	4	1	5	0.999	-0.497	-0.585
CFI1	15	0	3.602	4	1	5	0.956	-0.41	-0.546
CFI2	16	0	3.735	4	1	5	0.91	0.292	-0.848
GTL1	17	0	3.439	4	1	5	1.079	-0.465	-0.557
GTL2	18	0	3.133	3	1	5	1.046	-0.821	0.001
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: Author´s own processing

Table 25: Rating per indicator

	LOBSP 1	LOBSP 2	CFI 1	CFI 2	GTL 1	GTL 2	CC 1	CC 2	CC 3	PPE 1	DCI 1
Strongly agree	23	18	14	15	13	9	11	21	11	7	7
Agree	49	48	49	57	44	30	41	33	49	31	31
Neutral	13	14	18	12	19	28	26	22	20	32	23
Disagree	11	17	16	13	17	27	16	20	15	20	29
Strongly	2	1	1	1	5	4	4	2	3	8	8

Source: Author´s own processing

Table 26: Rating percentage per indicator

	LOBS P1	LOBSP 2	CFI1	CFI 2	GTL 1	GTL 2	CC1	CC2	CC3	PPE 1	DCI 1
Strongly agree	23.5%	18.4%	14.3	15.3	13.3	9.2%	11.2	21.4	11.2	7.1%	7.1%
Agree	50.0%	49.0%	50.0	58.2	44.9	30.6	41.8	33.7	50.0	31.6	31.6
Neutral	13.3%	14.3%	18.4	12.2	19.4	28.6	26.5	22.4	20.4	32.7	23.5
Disagree	11.2%	17.3%	16.3	13.3	17.3	27.6	16.3	20.4	15.3	20.4	29.6
Strongly	2.0%	1.0%	1.0%	1.0%	5.1%	4.1%	4.1%	2.0%	3.1%	8.2%	8.2%

Source: Author´s own processing

In governance constructs, respondents reflected that formal engagement which assumes business stakeholders responsibility and cross-functional communication to resolve data issues have stronger levels while team identity has lowest. In all governance related variables (Line-of-Business Stakeholders Participation (LOBSP) and Cross-Functional Integration (CFI) and Governance Team Leadership (GTL)), 73.5% and 73.5% as highest level of agree and strongly agree answers are shown with LOBSP1 indicator (business stakeholder involvement in formal engagement which assumes their responsibility) and with CFI2 (Data governance framework assumes cross-functional communication to resolve data issues outputs). In all governance related variables 39.8% as the lowest level of 'agree' and 'strongly agree' answers - is shown with GTL2 (Data governance stewards behave like a unified team).

In governance constructs, respondents think that Line-of-Business Stakeholders Participation (LOBSP) and Cross-Functional Integration (CFI) have higher levels than Governance Teal Leadership (GTL). First two have a similar average portion of 'agree' and 'strongly agree' answers (70.5% versus 68.9%) while the latter has that portion significantly lower (49.9%).

Respondents are of 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. Customer-Centric Orientation (CCO), with 73.5% average portion of agree and strongly agree answers versus 61.2% and 61.2% - CC1 (Customer focused functional teams work together, are aware of each other's responsibilities) has higher that portion than CC2 and CC3 (Rate of customer data being integrated, consolidated and used for analysis; Strategies and processes are explored for ways to differentiate and provide better customer experience with using customer metrics)

Dat 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% - Data Governance Span (DGS) constructs and Customer Centric Orientation (CCO) have a significantly higher average portion of 'agree' and 'strongly agree' answers compared to Data Compliance Innovation (DCI) and Privacy Project Efficiency (PPE).

Innovation in data compliance project is still having less negative ratings. The highest portion of disagreeing and strongly disagree answers is 31.7% in PP1 (privacy project efficiency) and especially 37.8% GTL2 (Data governance stewards behave like a unified team).

6.3. HYPOTHESES TESTING RESULTS AND DISCUSSION

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. The path coefficients can be interpreted similarly to the standardized beta weights in multiple regressions. Paths permit confirmation or rejection of hypotheses as well as the measurement of the strength of the relationship between dependent and independent variables. This is the case with SmartPLS tool as well (Hair et al., 2017).

Path coefficients are always standardized path coefficients. Given standardization, path weights, therefore, vary from -1 to +1. Weights closest to absolute 1 reflect the strongest paths. Weights closest to 0 reflect the weakest paths. The path coefficient value needs to be at least 0.1 to account for a certain impact within the model (Wetzels et al., 2009). Assessment of the path coefficient shows that all proposed hypotheses are supported, except for hypothesis H9. From the analysis, supported hypotheses are significant at least at the level of 0.05, have expected positive sign directions and consist of a path coefficient value (β) ranging from 0.109 to 0.500.

In SmartPLS in order to test the significant level, t-statistics for all paths are generated using the SmartPLS bootstrapping function. Path coefficients in PLS do not assume a normal, chi-square, or other known distribution. Therefore, the usual asymptotic significance levels cannot be computed. Rather, bootstrapped significance coefficients must be employed. In SmartPLS this requires running the model after requesting "Bootstrapping" rather than "PLS Algorithm" from the "Compute" button menu. As traditional statistical tests do not apply to PLS, bootstrapping has been used to derive average coefficients, standard errors, and t-values. Bootstrapping uses resampling methods to compute the significance of PLS coefficients. This way "bootstrapping" technique helps to gain the respective t-values to test for significance and based on such obtained t-statistics, the significant level of each relationship is determined (Kushary, Davison, & Hinkley, 2000).

Eventually, using the results from the path strength assessment, alongside its significant level assessment, the proposed hypotheses are accepted or rejected.

From the obtained results:

Customer-Centric Orientation (CCO) influence positively Data Compliance Innovation (DCI) ($\beta(b)=0.378$, $t=4.143$, $p=0$), therefore, Customer-Centric Orientation (CCO) leads to increase in Data Compliance Innovation (DCI) and H1 hypothesis is supported.

Data Governance Span (DGS) influence positively Privacy Project Efficiency (PPE) ($\beta(g)=0.500$, $t=6.696$, $p=0$, therefore, Data Governance Span (DGS) leads to increase of Privacy Project Efficiency (PPE) and H3 hypothesis is supported.

Governance Teal Leadership (GTL) influence positively Line-of-Business Stakeholders Participation (LOBSP) ($\beta(l)=0.279$, $t=2.864$, $p=0$), therefore, Governance Teal Leadership (GTL) leads to increase of Line-of-Business Stakeholders Participation (LOBSP) and H5 hypothesis is supported.

Governance Teal Leadership (GTL influence positively Cross-Functional Integration (CFI) ($\beta(i)=0.463$, $t=5.939$, $p=0$), therefore, Governance Teal Leadership (GTL) leads to increase of Cross-Functional Integration (CFI) and H6 hypothesis is supported.

In SmartPLS, the results of the PLS-SEM algorithm and the bootstrap procedure include the direct, the total indirect effect, the specific indirect effects, and the total effect. These outcomes, permit conducting a mediator analysis (Hair et al., 2017). Hair (2013a) describes the systematic mediator analysis process in PLS-SEM in more detail; also see (Nitzl, Roldan, & Cepeda, 2016) (Nitzl et al., 2016).

Mediation occurs when a third mediator variable intervenes between two other related constructs. More precisely, a change in the exogenous construct causes a change in the mediator variable, which, in turn, results in a change in the endogenous construct in the PLS path model. Thereby, a mediator variable is the underlying mechanism of the relationship between two constructs.

Analyzing the strength of the mediator variable's relationships with the other constructs allows calculating the strength of the mechanisms. SmartPLS supports to model and analyze mediators.

According to (Henseler et al., 2016), assessing the direct and indirect relationships between exogenous and endogenous latent variable is another important evaluation of a structural model.

The mediator analysis first examines the influence of the independent variable on the dependent variable. From the analysis dependent variable must be influenced by the independent variable. To test the mediating effect of the third variable, such variable is introduced as intervening or mediating variable, it is placed into the relationship between the independent and dependent variable.

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 effect also is tested in the post-hoc analysis

From the obtained results:

Customer Centric Orientation (CCO) is identified to influence Data Compliance Innovation (DCI) positively (β(a)=0.378, t=4.124) and has been influenced positively by Data Governance Span (DGS) (β(b)=0.471, t=6.31) (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(f)=0.328 to β(f')=0.193 and f' is not significant (t=1.558) (condition 2 fulfilled). Total indirect effect of Data Governance Span (DGS) - Customer Centric Orientation (CCO) - Data Compliance Innovation (DCI) relationship is significant (β(a)=0.135, t=2.238) (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.

Cross-Functional Integration (CFI) is identified to influence Line-of-Business Stakeholders Participation (LOBSP) positively (β(e)=0.332, t=2.816) and has been influenced positively by Customer Centric Orientation (CCO) (β(d)=0.33, t=4.67) (condition 1 fulfilled). The introduction of the mediating variable reduces the coefficient value between Customer Centric Orientation (CCO) – Line-of-Business Stakeholders Participation (LOBSP) relationship from β(c)=0.267 to β(c')=0.154 and c' is not significant (t=1.351) (condition 2 fulfilled). Total indirect effect of Customer Centric Orientation (CCO) - Cross Functional Integration (CFI) - Line-of-Business Stakeholders Participation (LOBSP) relationship is significant (β(de)=0.109, t=2.172) (condition 3 fulfilled). Therefore, there is the full mediating effect of Cross-Functional Integration (CFI) and it is the underlying mechanism of the relationship Customer Centric Orientation (CCO) - Line-of-Business Stakeholders Participation (LOBSP), and H4 is marginally supported.

Line-of-Business Stakeholders Participation (LOBSP) is identified to influence Privacy Project Efficiency (PPE) positively (β(m)=0.31, t=2.864) and has been influenced positively by Governance Teal Leadership (GTL) (β(l)=0.279, t=2.864) (condition 1 fulfilled). The introduction of the mediating variable reduces the coefficient value between Governance Teal Leadership (GTL) – Privacy Project Efficiency (PPE) relationship from β(n)=0.192 to β(n')=0.087 and n' is not significant (t=0.126) (condition 2 fulfilled). However, the total indirect effect of Governance Teal Leadership (GTL) – Line-of-Business Stakeholders Participation (LOBSP) - Privacy Project Efficiency (PPE) relationship is not significant (β(lm)=0.087, t=1.772) (condition 3 not fulfilled). Therefore, there is no full mediating effect of Line-of-Business Stakeholders Participation (LOBSP) and it is not an underlying mechanism of the relationship Governance Teal Leadership (GTL) – Privacy Project Efficiency (PPE), and H7 is not supported.

Cross-Functional Integration (CFI) is identified to influence Privacy Project Efficiency (PPE) positively (β(j)=0.300, t=2.353) and has been influenced positively by Governance Teal Leadership (GTL) (β(i)=0.463, t=5.939) (condition 1 fulfilled). The introduction of the mediating variable reduces the coefficient value between Governance Teal Leadership (GTL) – Privacy Project Efficiency (PPE) relationship from β(n)=0.204 to β(n')=0.087 and n' is not significant (t=0.692) (condition 2 fulfilled). Total indirect effect of Governance Teal Leadership (GTL) - Cross Functional Integration (CFI) - Privacy Project Efficiency (PPE) relationship is significant (β(ij)=0.139, t=2.09) (condition 3 fulfilled). Therefore, there is the full mediating effect of Cross-Functional Integration (CFI) and it is the underlying mechanism of the relationship on Governance Teal Leadership (GTL) - Privacy Project Efficiency (PPE), and H9 is supported.

Based on (Baron & Kenny, 1986) guidelines, this study concludes that effective commitment partially has mediated the relationship between satisfaction and continuous knowledge sharing intention.

Moderation describes a situation in which the relationship between two constructs is not constant but depends on the values of a third variable, referred to as a moderator variable. When moderation is present, the strength or even the direction of a relationship between two constructs depends on a third variable. Moderating relationships are hypothesized in advanced and specifically tested in SEM PLS. If the moderator (or predictor) is formatively measured, the two-stage approach should be selected as the calculation method. If the moderator (and predictor) are both reflectively measured, it is possible to choose any of the three calculation methods depending on your research objective as the difference is relatively small between the approaches in such case. Two-stage has the highest power and it is the most likely approach to detect a significant interaction. Orthogonalizing has the smallest bias and the interaction effect size is most correct and it maximizes the explained variance in your dependent variable. Product-Indicator approach has no particular advantages. As the sample size is small, the focus was on statistical power and hence the two-stage approach is selected. (Henseler & Wynne Chin, 2010). The testing of the moderating relationship depends on whether the researcher hypothesizes whether one specific model relationship or whether all model relationships depend on the scores of the moderator (Wynne Chin, Marcolin, & Newsted, 2003).

In this research only one relationship was tested where the predictor is, the dependent variable is, and moderator variable. The results show that there is a significant relationship where Cross-Functional Integration (CFI) is a predictor, Privacy Project Efficiency (PPE) is dependent variable and Line-of-Business Stakeholders Participation (LOBSP) is a moderator (β(k)=0.142, t=2.014). Therefore, there is the moderating effect of Line-of-Business Stakeholders Participation (LOBSP) on Cross-Functional Integration (CFI) - Privacy Project Efficiency (PPE) relationship and H2 is supported.

Table 27: Hypotheses testing results.

H1: Customer-Centric Orientation (CCO) leads to increase in Data Compliance Innovation (DCI)	Supported
H2*: There is the mediating effect of Customer-Centric Orientation (CCO) on Data Governance Span (DGS) – Data Compliance Innovation (DCI) relationship.	Supported
H3*: Data Governance Span (DGS) leads to an increase of Privacy Project Efficiency (PPE)	Supported
H4: There is the mediating effect of Line-of-Business Stakeholders Participation (LOBSP) on Customer Centric Orientation (CCO – Cross-Functional Integration (CFI) relationship.	Marginally Supported
H5*: Governance Teal Leadership (GTL) leads to an increase of Line-of-Business Stakeholders Participation (LOBSP)	Supported
H6*: Governance Teal Leadership (GTL) leads to an increase in Cross-Functional Integration (CFI)	Supported
H7: There is the mediating effect of Line-of-Business Stakeholders Participation (LOBSP) on Governance Teal Leadership (GTL) - Privacy Project Efficiency (PPE) relationship.	Supported
H8: There is the moderating effect of Line-of-Business Stakeholders Participation (LOBSP) on Cross-Functional Integration (CFI) - Privacy Project Efficiency (PPE) relationship.	Supported
H9: There is the mediating effect of-of Cross-Functional Integration (CFI) on Governance Teal Leadership (GTL) - Privacy Project Efficiency (PPE) relationship.	Not supported

*Source: Author´s own processing (*The hypotheses of this research are divided into two parts: primary hypotheses (marked with asterisk *) that primary guided this research and secondary hypotheses that are included due to the exploration-driven nature of this study).*

The hypothesized direct relationship with the strongest path is associated with H3 (DGS) – (PPE) (β(g)=0.500). The direct relationship with the weakest path is associated with H5 (GTL) – (LOBSP) (β(l)=0.279). On a similar level of strength with the strongest one is the second strongest one – that is associated with H6 (GTL) – (CFI) (β(i)=0.463)

The hypothesized indirect relationship with the strongest path is associated with H9 (GTL) – (CFI) – (PPE) (β(ij)=0.139)). The indirect relationship with the weakest path is associated with H7 (GTL) – (LOBSP) – (PPE) (β(lm)=0.087), which made H7 not supported. Although the introduction of (LOBSP) as mediator decreased independent – dependent relationship for more than double (β(n)=0.192 to β(n')=0.087). On a similar level of strength with the strongest one is the second strongest one – that is associated with H2 (DGS) – (CCO) – (DCI) (β(ab)=0.136)

Findings can be divided into four sections:

In the first section, the role of governance span and customer-centricity in seen active in achieving two seemingly conflicting objectives in compliance efforts, innovation and efficiency at the same time:

First section results:

- From (DGS) there are direct relationships with strong paths associated with both data compliance related variables, (PPE) ((g)=0.500)) and (DCI) ((b)=0.328).

- From (DGS) there is a stronger direct relationship with path associated with (PPE (β(g)=0.500)) than with (DCI) (β(b)=0.328).

- However, from (CCO) there is a strong direct relationship with path associated with (DCI) (β(b)=0.378)).

- From (DGS) there are direct relationships with strong paths associated with both data compliance related variables, (PPE) ((g)=0.500)) and (DCI) ((b)=0.328) and stronger path associated with (PPE) (β(g)=0.500)) than with (DCI) (β(b)=0.328). However, there is an indirect relationship that is associated with (DGS) – (CCO) – (DCI) (β(ab)=0.136) and that is the second strongest indirect relationship in the model.

First section comments:

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 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).

In the second section, the introduction of leadership and its influence on governance span showed the impact:

Second section result:

- From (DGS) there are direct relationships with strong paths associated with both (DGS) lower order constructs, (CFI) (β(i)=0.463)) and (LOBSP) (β(l)=0.279).

- From (GTL) there is a much stronger direct relationship with path associated with (CFI) (β(i)=0.463)) than with (LOBSP) (β(l)=0.279).

Second section comment:

As it is so strong direct mechanism of increase of Privacy Project Efficiency (PPE) further exploration of Data Governance Span (DGS) showed how it is possible to influence change in this construct - Governance Teal Leadership (GTL) leads to the increase of both of Data Governance Span subconstructs at the same time: Cross-Functional Integration (CFI) and Line-of-Business Stakeholders Participation (LOBSP).

As it is a direct mechanism of increase of Data Governance Span (DGS) further exploration of Governance Teal Leadership (GTL) showed the difference in how it is possible to influence change in this construct. While Governance Teal Leadership (GTL) leads to the increase of both of Data Governance Span subconstructs at the same time, Cross-Functional Integration (CFI) and Line-of-Business Stakeholders Participation (LOBSP)), it has a much higher impact on the increase of the former than on the later one.

In the third section, the relations between leadership, efficiency, and governance have more findings:

Third section result:

- From (DGS) to (PPE) are no indirect relationships from both (DGS) lower order constructs, but only with one of them (CFI). This is hypothesized indirect relationship with the strongest path in the model associated with H9 (GTL) – (CFI) – (PPE) (β(ij)=0.139)).

- There is a significant relationship where (CFI) is a predictor, (PPE) is dependent variable and (LOBSP) is a moderator (β(k)=0.142, t=2.014).

Third section comment:

At the same time, Governance Teal Leadership (GTL) leads to the increase of Privacy Project Efficiency (PPE) through the 'stronger' Data Governance Span subconstruct (Cross-Functional Integration (CFI)), but not through the 'weaker' one - Line-of-Business Stakeholders Participation (LOBSP)).

Further exploration of this 'stronger' data governance span variable (Cross-Functional Integration (CFI)) and the way how it leads to increase of Privacy Project Efficiency (PPE) showed there is the use of the 'weaker' data governance subconstruct as it increases the strength of the relationship. The impact of Cross-Functional Integration (CFI)) on Privacy Project Efficiency (PPE) can be strengthened trough Line-of-Business Stakeholders Participation (LOBSP).

In the fourth section, the relations between customer-centricity, innovation and governance have more findings:

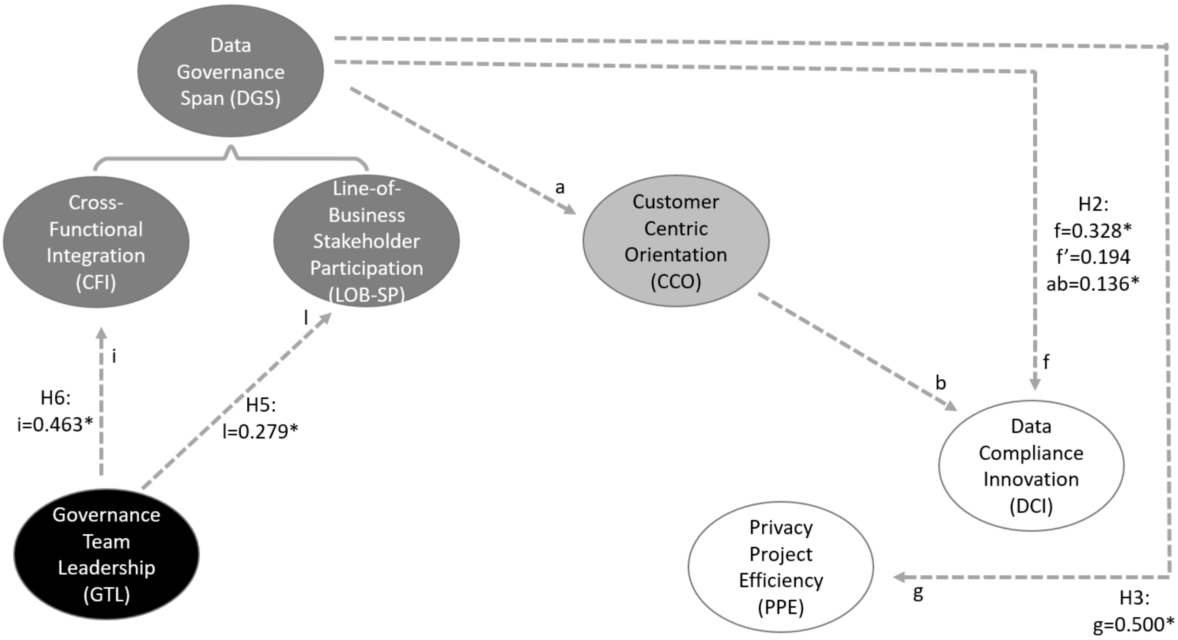
Forth section result:

- There is indirect relationship that is associated with (CCO) - (CFI) - (LOBSP) (β(de)=0.109). The supported hypothesized indirect relationship associated with H4 (CCO) (CFI) (LOBSP) is to be taken by caution as it is close to 0.1 level

Forth section comment:

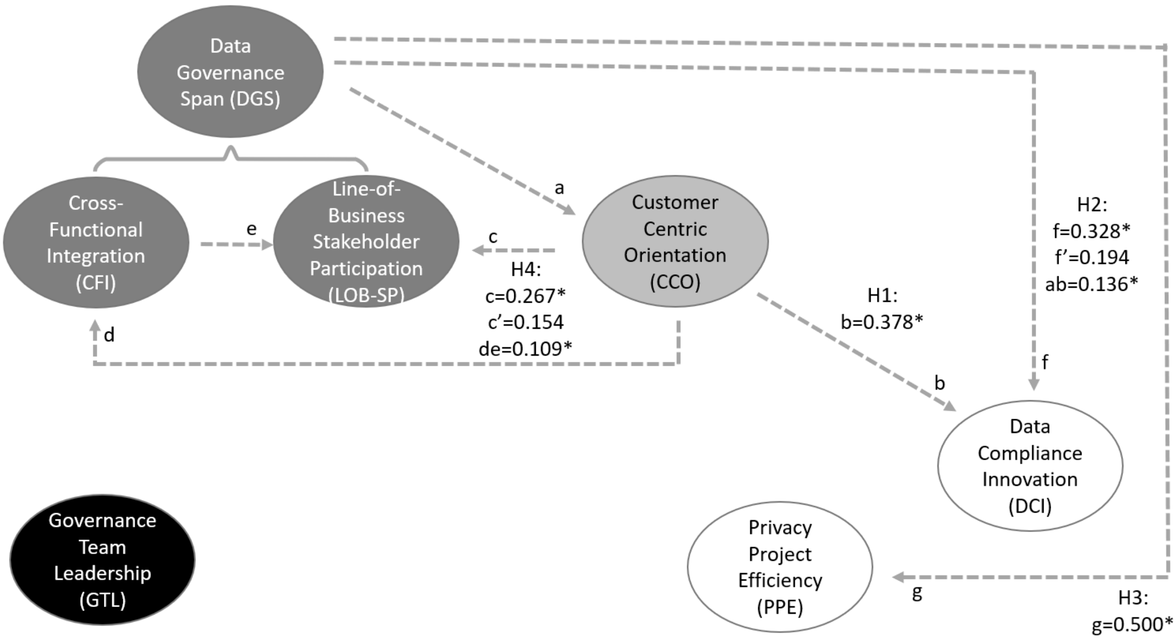
Also, Customer Centric Orientation (CCO) can lead to increase of the moderator Line-of-Business Stakeholders Participation (LOBSP) - through the other data governance span construct - Cross-Functional Integration (CFI).

Figure 12: Primary hypotheses model results



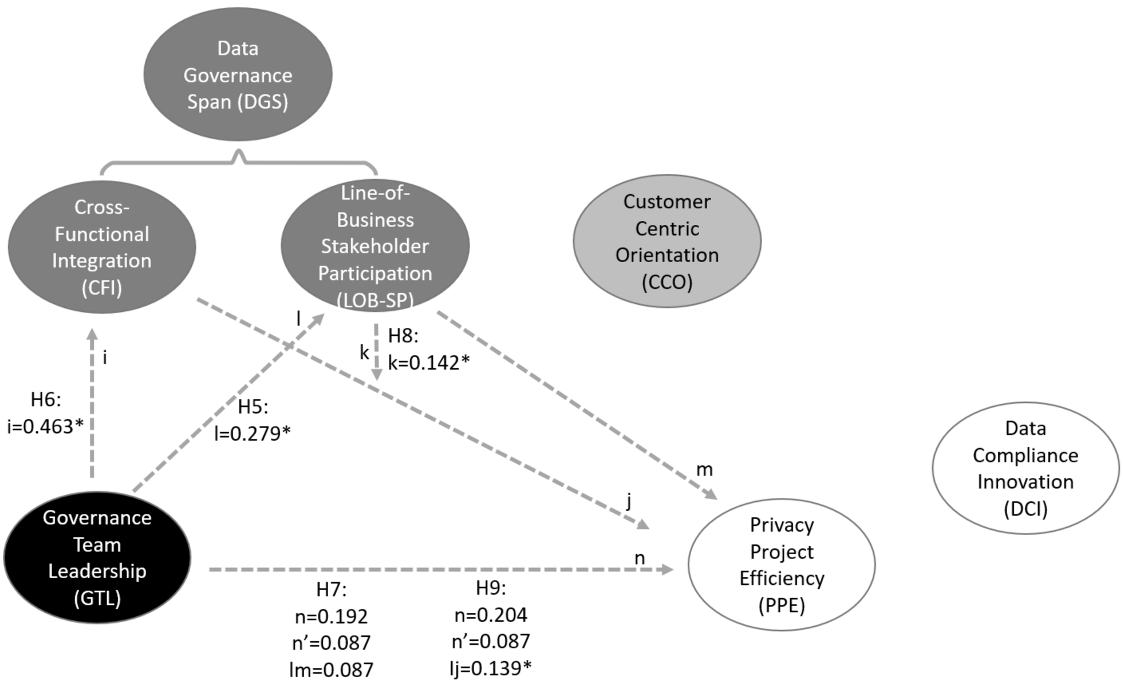
Source: Author´s own processing

Figure 13: Full model - section A results



Source: Author´s own processing

Figure 14: Full model - section B results



Source: Author´s own processing

Table 28: Hypotheses testing results

	Original	**Sample**	**Standard**	**T Statistics**	**P Values**
H1					
CCO -> DCI / H1(b)	0.378	0.384	0.091	4.143	0
H2*					
DGS -> CCO / H2(a)	0.471	0.47	0.075	6.31	0
CCO -> DCI / H2(b)	0.378	0.384	0.091	4.143	0
DGS -> DCI /H2(f)	0.328	0.329	0.112	2.923	0.004
DGS -> DCI /H2(f')	0.193	0.189	0.121	1.558	0.113
DGS -> DSI /H2(ab)	0.135	0.132	0.060	2.238	0.026
H3*					
DGS -> PPE /H3(g)	0.500	0.500	0.0.75	6.696	0
H4					
CFI -> LOBSP /H4(e)	0.332	0.33	0.118	2.816	0.005
CCO -> CFI /H4(d)	0.33	0.339	0.071	4.67	0
CCO -> LOBSP / H4(c)	0.267	0.267	0.095	2.809	0.005
CCO -> LOBSP / H4(c')	0.154	0.152	0.114	1.351	0.177
CCO -> CFI -> LOBSP	0.109	0.113	0.05	2.172	0.019
H5*					
GTL -> LOBSP / H5(l)	0.279	0.28	0.098	2.864	0.004
H6*					
GTL -> CFI /H6(i)	0.463	0.462	0.078	5.939	0
H7					
GTL -> LOBSP / H7(l)	0.279	0.28	0.098	2.864	0.004
LOBSP -> PPE / H7(m)	0.31	0.301	0.118	2.624	0.009
GTL -> PPE /H7(n)	0.192	0.178	0.125	1.532	0.126
GTL -> PPE /H7(n')	0.087	0.08	0.126	0.692	0.49
GTL -> LOBSP -> PPE	0.087	0.086	0.049	1.772	0.077
H8					
Moderating Effect 1 -> PPE	0.142	0.148	0.071	2.014	0.045
H9					
GTL -> CFI /H9(i)	0.463	0.462	0.078	5.939	0
CFI -> PPE /H9(j)	0.3	0.311	0.128	2.353	0.019
GTL -> PPE /H9(n)	0.204	0.197	0.113	1.809	0.071
GTL -> PPE /H9(n')	0.087	0.08	0.126	0.692	0.49
GTL -> CFI -> PPE /H9(ij)	0.139	0.145	0.067	2.09	0.037

*Source: Author´s own processing (*The hypotheses of this research are divided into two parts: primary hypotheses (marked with asterisk *) that primary guided this research and secondary hypotheses that are included due to the exploration-driven nature of this study).*

7. CONCLUSION, LIMITATIONS AND FURTHER RESEARCH

This final segment of the research project summarizes the main areas covered in the dissertation and gives a final comment adjusted with sections on the research limitations and suggestions and recommendations for future work.

7.1. CONCLUSION

This dissertation aims to shed light on the economics of data, levels, and aspects of utilized benefits associated with their economic potential in the data economy, levels and aspects of their efficient control for compliance purposes. The research project integrates theories from microeconomics, organizational design, marketing and organizational psychology with several practical inter-relating state-of-the-art business and research problem domains around data compliance. This integrative perspective has the aim to provide a useful tool for managers needing to assess the likelihood of effective strategies - and help them proactively design interventions. The field has weaknesses in an appropriate connection with causal variables, which led to this multi-variable exploration-driven quantitative research.

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 - while information can be stored, replicated and transmitted much faster and at a much lower cost. Technology progress brings increasing opportunities for successive interactions in order to achieve profitable customer relationships. The decrease in the cost of storing data has made it possible to capture, save, and analyze a much larger amount of information. Collecting rich datasets of customers allows better targeting of narrower specific markets. It brings down advertising costs while improving consumer loyalty and revenue with analytics. These analytics are on how to provide accurate customer, pricing and risk data, ad hoc, in a price sensitive, competitive landscape, based on accurate and real-time insights. Organizations start monetizing these data as behavioral data generated on the platform.

However, there are requirements for control that come with all these welfare effects – and lifecycles of all these data need to be known, alongside undoubted trust in the data. Regulators started to demand such data lifecycles and an important market and customer-related decisions are based upon them as well.

The study argues if compliance spending then can also generate additional value. Compliance costs become more significant, and not limited anymore to only regulated industries. Data related regulations are more frequent and will further increase with ongoing and focused development of economic thinking related to the role of data in the digital economy.

However, such thinking is still lagging behind advances in data technology at this moment. Thus, the economics of data privacy, data compliance or data utility are still not fully understood (Duch-Brown, 2017); neither is there a sufficient amount of proven strategies that enterprises could rely on. First regulations in their initial versions just appeared in recent years and much more is expected to come. Markets are still poorly understood by authorities, and as their knowledge increases, we can expect new ways of regulating the use of data ownership, big data, data trade, data market competition, in order to attain other public goals (Capobianco, 2016).

Simple compliance basic requirement fulfillment is not a strategy of readiness for the data revolution underway and for a considerable number of regulations ahead. Organizations should, therefore, have a compliance-triggered but competitive advantage-driven solid and repetitive strategy - and a clear action plan to execute.

While fulfilling compliance requirements, it would be beneficial to find mechanisms that bring positive influences in two self-contradicting directions, innovation and efficiency, 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). Regulation demands that it is necessary to place in front of customers an interactive control platform for agreements between data holders (firms) and data subjects (customers). Agreements may selectively protect or disclose different types of personal data while utilizing granular measures of these data to optimize privacy trade-offs and add value for customers. Making data, permissions, and controls accessible to customers, and sustained personal engagement and ongoing success in addressing exact customer desire in these agreements on the platform - will generate loyalty.

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 between consumers and organisations adopted to superior customer-centric engagement model alongside compliance-driven activities (Kumar et al., 2010). Ideally then, the compliance effort, if done right, should lead to innovative new business initiatives, which otherwise would never be funded anyway. Data-driven innovations are becoming an increasingly vital feature of our societies, leading to growing data services dependence by individual consumers or economic subjects.

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 fulfillment - can be a differentiator. In modern times, the ability to quickly adjust to frequent changes in response market or compliance requests raises the importance of operational efficiency (Slack et al., 2013).

Moreover, speed is especially significant in the modern competitive global environment as time-related project failure is frequently connected with the unrecoverable loss of revenue (Scott-Young & Samson, 2009). The firm will outperform competitors if core processes become faster, eliminate waste and reduce costs, besides basis in appropriate technology innovation adapted (M. Porter, 1998).

EU companies could then indeed use data compliance and GDPR regulation as a competitive advantage, and as a means for innovation and further efficiency, clearly resulting in data regulation associated benefits exceeding their costs to comply.

Such data related compliance requests are challenged with the slow movement of data and information management from low-level operations towards managerial functions. On the other hand, the path towards GDPR-like compliance requires a coordinated strategy involving different organizational entities including legal, human resources, marketing, security and IT and their integration. An end-to-end approach to the assets of all data and customers data - is a necessary prerequisite for effective regulation responses. Data compliance is an opportunity to achieve commercial long-term benefits if it evolves into broader efforts. Data compliance can be a perfect catalyst or first step towards establishing a common data model for customer data and party data. Extension of this model into an idea of enterprise data as a service - fuels customer-facing functions operations and leads to competitive advantage (Mantelero, 2016).

In such a new data compliance-driven environment, this research project explores ways for achieving adequate vertical strategies, combined as well with horizontal strategies of integration - which has been a challenge for managers for a long time (Galbraith & Lawler, 1993) and (M. Porter, 1998) (Mintzberg, 1979). Rather than in the technological field, the study looks into organizational practices for empirical proof, where multiple predictor, mediator, and moderating variables were measured in order to offer a range of potential managerial interventions. Customer centricity and integration of customer information for advanced analytics and data usage cannot be achieved without modernizing the existing line of business systems. The reason for information issues lies in the fact that the greatest challenge to success is not so much technological as organizational.

For Niemi and Laine (2016) the best practices from strategic management, business process management, risk management, and IT governance are combined in the information governance concept. Information aspects nowadays clearly override the domain of information technology (Kooper et al., 2011) – demanding governance-driven constant improvement in communication between departments (horizontal), and between management levels (vertical) (Orr, 1998). Such governance arrangements can compensate for the rigidity of the organizational structure and help organizations to achieve two seemingly conflicting objectives, that arguably could not be combined successfully at the same time – efficiency and innovation (Korhonen et al., 2013).

Despite the growing importance of such holistic cross-organization initiatives, many organizations continue to struggle with their governance programs as they resist, seeing such program as a large-scale undertaking, 'too big change', and transformational (Mittal & Dhar, 2015). Resistance against organizational change is the dominant reason for the inefficiency of operations while leading the rational change implementation. Organizations need to increase efficiency in these projects in order to survive in the present dynamic environment (Drucker, 2009). As many researchers have demonstrated, leaders and influencers play a major role in IT implementation success or failure, and there is a need for specifications of program leader behaviors and suggestions to management.

The data governance stewards are necessary leaders in the context of enterprise-wide governance. A leadership profile is necessary for a governance team as it is impacted by high requirements on collaborating skills and ability to influence, in both business and technology teams across business units (Villar, 2009).

As it was shown in this work, fortunately there are organizational interventions that provide value in multiple directions in order to address the mentioned challenges and stated research problems. The complex nature of these interventions raises concerns about the time frame for their completeness and urgency for their immediate start.

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. The research proves this in the GDPR regulation case. The former is achieved in customer-centric orientation as an active parallel strategy in addition to the governance span strategy. The customer-centric operating model even has an additional positive impact on the governance span itself, as it proposes organizational design changes and integration of customer-facing functions and metrics - contributing to the overall cross-functional governance integration.

If it is necessary to increase the span – governance team leadership should be called for (leadership in the building of team identity, communication and knowledge transfer in the work schedule). When the span of data governance is further substantiated for managers - it is visible that the horizontal span (cross-functional integration) is the primary way of how governance team leadership positively impacts project efficiency. To adopt it within a data governance framework there must be enabled an intensive share of information and ideas between functions and cross-functional communication to resolve data issues. Vertical span or line-of-business stakeholders' participation can increase the strength of this impact. It consists of involving business stakeholders in formal engagement which assumes their responsibility and in the formulation of objectives, evaluation of results and use of outputs.

The aerospace or transportation industries, although represented by a small number of companies, seem 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. Consulting companies, although advising all others to do so, do not use governance frameworks as extensively as their customers.

E-Commerce and retail are highly focused on innovation in data regulation and extensively use data governance span, but do not obtain the same results in project efficiency. Technology, software or Internet companies do not involve line-of-business stakeholders in governance frameworks, especially in the formulation of objectives, evaluation of results and use of outputs. The telecommunication industry is not using governance team leadership and has a lower efficiency in data compliance projects.

Firms in Central and Eastern Europe did not use innovation enough in data compliance and have the lowest leadership of data governance teams, especially in communication, knowledge transfer and work schedule. Southern European firms have the highest cross-functional integration and horizontal data governance span, however, their governance teams do not have an identity as much as in other regions. Western European 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.

Based on an extensive review of the previous literature, 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 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 not only governance, but 'fruitful' data strategy as well.

The conceptual framework presented is based on three major grounding theories. The primary focus was the organizational theory of a horizontal and vertical linking mechanism from Mintzberg (1979) and Galbraith (1974). Primarily, the concept is incorporated into the 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 theories from leadership and marketing, transformational leadership theories from Bass (1985) and Burns (2003), and a market orientation theory from Narver and Slater (1990) and Jaworski and Kohli (1993).

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).

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.

Investigating 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, 2013). It seems obvious that if we manage to reach an equilibrium at which the interests of consumers, firms and regulatory principles are aligned - the gains for the economy and the boost for innovation will be significant (Alonso, 2014).

7.2. FURTHER RESEARCH

The focus of this research was exploration, causal modeling and theory building, rather than theory confirmation. In particular, the study used a complex model with hierarchical components (higher and lower order constructs), latent (unobserved) variables, chains of effects (mediation) and moderation (Lowry & Gaskin, 2014). The natural next step would be theory confirmation of the whole model or some of its sections, by using some of the variance based SEM methods and a larger amount of records. No individual-level measures that are empirically validated are found for constructs rationalized in this research. As a result of the process of gathering similar existing measures while covering the theoretical domain of new constructs, 'raw material' is obtained for future more extensive measures. Further research might complement this work through a more thorough process of building constructs, its rationalization, and operationalization with a higher number of indicators. Limited space of high order general theoretical concepts is operationalized in the instrument. 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 focus of this research is cross-functional horizontal governance span which most often intersects with a span over other domains: system, projects, subject areas and especially processes. Similar research for another domain would contribute to the further generalization of these findings. The existing model could be validated in some environments, where organizational practices have a high and complex impact, not necessarily governance or compliance related. For example, in the ongoing disrupted organization of software development, do vertical integration (developers' exposure to business users) and horizontal integration (development team with tighter bonds) provide innovation and project efficiency, and what is the role of leadership?

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. For instance, aerospace and transportation scored the highest, while e-commerce and retail scored the lowest across almost all variables.

Effective and high-quality data stewardship is possible only if it also becomes part of the corporate culture and as with any corporate culture, top managers play a crucial role in institutionalizing it (Weber et al., 2009). The cultural aspect was not taken into consideration in this research, although it is expected that a big part of unexplained dependent constructs can be covered this way in additional research.

A shape of the data economy is understood only within a gradual and still ongoing process, although its signs are everywhere. The rapid emergence of data and personal data as an asset in business processes, enabled by the development of information and communication technology (ICT), calls for factual, empirical analysis. Further understanding of intra-organizational dynamics and mechanisms to gains 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 is a gap between existing economic models of data ownership, use and access, and the reality of markets that are driven by data. There are no strongly-argumented policy solutions yet and more research is required to bring economics up to speed with these questions

(Duch-Brown, 2017). GDPR and PSD2 regulations are facing a new and complex scenario, with lots of momentum on several fronts in advanced digital economy developments. These changes may lead to that regulation, as we know it, has to adapt to new times, and adaptability and flexibility will have to be explored over the years. These will bring opportunities to adopt findings from this research or to validate them in a new changed setup.

7.3. LIMITATIONS OF EXISTING VERSION OF DISSERTATION

Three major limitations of the study are a number of items in a measure, sample size, and new wide constructs conceptualized (as a result of theoretical integration), where a narrow piece of them is operationalized.

All three are the result of the decision that the focus of the research is rather developmental, exploration, causal modeling, and theory building, rather than theory confirmation. All three are addressed by a decision on the statistical method, which does not necessarily entail strong prior theories and established operationalizations, but does support constructs with single-items findings and supports small data sets (Gefen et al., 2000; Teo, Oh, Liu, & Wei, 2003).

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). This was not a feasible option considering the complex model. Responses are asked from senior members associated with data management, 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 in order to ensure the collection of a sufficient number of answers from the right people. Additionally, keeping a measure short is an effective means of minimizing response biases (Schriesheim & Eisenbach, 1995) as scales with too many items can create problems with respondent fatigue or response biases.

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, and that there is only one or holistically one, characteristic being referred to (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. Abstract constructs, on the other hand, could mean different things to different raters. 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 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 all aspects and individual preferences of 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 impact respondents in that they tend to differentially weight the relevant aspects in order to provide an overall summary single rating providing biased results for individual responses. In order to help respondents to automatically consider different aspects of the construct and be immediately aware of the full scope of the concept, the operational definitions used pointed this out in a comprehensive and yet clear way.

When the existing scales were carefully scrutinized across a range of research domains, it was found their items are often semantically similar. Constructs in business and management research are often seen with semantically identical and therefore redundant items, resulting from pressure to maximize the internal consistency of scales. This work evidenced that as it is based on the integration of concepts from different business and management areas while focused on minimization of scale. This further motivated the researcher to present a reduction in the number of items in order to avoid one part of the domain being oversampled (G. Smith & McCarthy, 1995) and showing 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, Leung, & Lee, 2002). Finally, two single item constructs had secondary importance in the study setting and the employment of single-item measures is justifiable (Drolet & Morrison, 2001; Nagy, 2002)

Finally, variance-based SEM was selected as a statistical method as it is dedicated to theory exploration and does support constructs with single-items and has flexible distributional assumptions which could result in more reliable findings (Gefen et al., 2000). However, scales with too few items may lack content and construct validity, internal consistency and test-retest reliability (Kenny, 1975), with single-item scales particularly being disposed to these problems (Hinkin, 1995). This remains a limitation of the study.

Sample size:

The larger sample size is needed to appropriately conduct tests of statistical significance, powerful statistical tests and confidence in results. However, obtaining large samples can be very costly. Responses are asked from senior members associated with data management, governance or compliance teams. Internal leaders have roles of data governance heads, leaders, managers, and directors. They are considered as 'high profiles', and in senior management positions, many do not take time to fill in online surveys. This triggered the decision on minimization of survey questions 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 (Teo 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 within the theoretical background section of this dissertation, while the conducted process of literature review provides justification for their usage. 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. The research generally commences with very wide theoretical concepts, where eventually a very narrow piece of them is operationalized. In the section related to governance team leadership, the need to address change management resistance was associated with two concepts that intersect with leadership theory - building team identity, and knowledge sharing and communication. This is just a small subset of potential behavioral or influence driven leadership strategies which are not necessarily the most important sources of leadership driven behaviors or influence in a given context. Similarly, innovation in data compliance was linked with customer engagement and interaction orientation, and privacy accountability reconciliation with project management efficiency. It gives an opportunity to other researchers to compare these results with other selection of concepts.

Some of the constructs still do not have validated scales and were operationalized from operational definitions built within this project.

The statistical method in this research is variance-based SEM. This method is dedicated to theory exploration rather than confirmation and 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

Some other limitations:

Reverse-scored items are not used in the data collection, as a decision was made to minimize the number of questions in the survey. Reverse-scored items are a useful tool in decreasing response pattern bias. However, as Jackson at al. (1993) claim, they are in a similar way shown to reduce the validity of questionnaire responses and may introduce systematic error to a scale which may result in an artifactual response factor consisting of all negatively-worded items (Harvey, Billings, & Nilan, 1985). Anonymity and a short survey were used instead to address response pattern bias.

The limitations of quantitative research methods apply to this study. It does not account for the range of people's thoughts or perceptions about what is being evaluated. Similarly, the limitation of the survey as a research instrument is that it may lack depth and may have provided limited information.

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