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Modelling the simultaneous effects of intellectual capital and knowledge management on the organisational performance of Finnish companies

Master's Thesis

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ABSTRACT

Author: Kalle Eerikäinen **Subject:** Modelling the simultaneous effects of intellectual capital and knowledge management on the organisational performance of Finnish companies	
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The aim of this study was to contribute to the current knowledge-based theory by focusing on a research gap that exists in the empirically proven determination of the simultaneous but differentiable effects of intellectual capital (IC) assets and knowledge management (KM) practices on organisational performance (OP). The analysis was built on the past research and theoreticised interactions between the latent constructs specified using the survey-based items that were measured from a sample of Finnish companies for IC and KM and the dependent construct for OP determined using information available from financial databases. Two widely used and commonly recommended measures in the literature on management science, i.e. the return on total assets (ROA) and the return on equity (ROE), were calculated for OP. Thus the investigation of the relationship between IC and KM impacting OP in relation to the hypotheses founded was possible to conduct using objectively derived performance indicators. Using financial OP measures also strengthened the dynamic features of data needed in analysing simultaneous and causal dependences between the modelled constructs specified using structural path models. The estimates were obtained for the parameters of structural path models using a partial least squares-based regression estimator. Results showed that the path dependencies between IC and OP or KM and OP were always insignificant when analysed separate to any other interactions or indirect effects caused by simultaneous modelling and regardless of the OP measure used that was either ROA or ROE. The dependency between the constructs for KM and IC appeared to be very strong and was always significant when modelled simultaneously with other possible interactions between the constructs and using either ROA or ROE to define OP. This study, however, did not find statistically unambiguous evidence for proving the hypothesised causal mediation effects suggesting, for instance, that the effects of KM practices on OP are mediated by the IC assets. Due to the fact that some indication about the fluctuations of causal effects was assessed, it was concluded that further studies are needed for verifying the fundamental and likely hidden causal effects between the constructs of interest. Therefore, it was also recommended that complementary modelling and data processing measures be conducted for elucidating whether the mediation effects occur between IC, KM and OP, the verification of which requires further investigations of measured items and can be build on the findings of this study.

TIIVISTELMÄ

Tekijä: Kalle Eerikäinen
Työn nimi: Aineettoman pääoman ja tietojohtamisen simultaanisten vaikutusten mallinnus suhteessa suomalaisten yritysten organisatoriseen suoriutumiseen

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Avainsanat: aineeton pääoma, aineettoman pääoman varallisuuslajit, aineettomat resurssit, arvonmuodostus, bootstrap, dynaaminen kyvykkyys, kokonaispääoman tuotto, luottamusväli, oman pääoman tuotto, organisaation suoriutuminen, osittainen pienimmän neliösumman menetelmä, polkurakennemallinnus, tietojohtaminen, tietojohtamisen käytännöt.

Tämän opinnäytetutkimuksen tavoitteena oli täydentää tietoperusteiseen näkökulmaan pohjaavaa teoriaa ja osoittaa empiirisesti aineettoman pääoman tekijöiden ja tietojohtamisen käytäntöjen yhdenaikaiset mutta eroteltavissa olevat vaikutukset organisatoriseen suoriutumiseen. Aiempaan tutkimukseen perustuen ja teoretisoituja vuorovaikutussuhteita hyödyntäen suoritettiin mallinnusperusteinen analyysi, jossa otannalla valituista suomalaisista yrityksistä aiemmassa kyselytutkimuksessa kootuilla tietojohtamisen ja aineettoman pääoman tunnuksilla selitettiin yritysten suoriutumista, jota kuvattiin taloudellisista tietokannoista kohdeyrityksille määritetyillä suoriutumista kuvaavilla indikaattoreilla. Suoriutumismuuttujana käytettiin joko kokonaispääoman tai oman pääoman tuottoa, jotka ovat laajalti hyödynnettyjä ja johtamisen tieteenalan tutkimuksissa yleisesti suositeltuja taloudellisen suoriutumisen tunnuslukuja. Siten tietojohtamisen ja aineettoman pääoman välisten riippuvuuksien ja niiden organisatoriseen suoriutumiseen kohdistuvien vaikutusten selvittäminen suhteessa tutkimushypoteeseihin oli mahdollista suorittaa käyttäen objektiivisesti määritettyjä suoriutumisindikaattoreita. Taloudellisten suoriutumismuuttujien käyttö vahvisti myös aineiston dynaamisia ominaisuuksia, mitä tarvittiin polkurakennemallinnuksen avulla määritettyjen rakennetekijöiden välisten kausaaliriippuvuuksien analysointiin. Polkurakennemallien parametrit estimoitiin osittaisen pienimmän neliösumman menetelmän regressioestimaattorilla. Tulokset osoittivat, että polkuriippuvuudet aineettoman pääoman ja organisatorisen suoriutumisen sekä tietojohtamisen ja organisatorisen suoriutumisen välillä eivät olleet merkitseviä, kun analyysi suoritettiin puhdistettuna muista muuttujien välisistä vuorovaikutuksista tai simultaanisen mallinnuksen epäsuorista vaikutuksista, mikä oli yhtäpitävää kummankin suoriutumisindikaattorin tapauksessa. Suoriutumista selittävien rakennetekijöiden välillä riippuvuus oli sitä vastoin erittäin voimakasta ja säilytti merkitsevyytensä kaikissa simultaanisen mallinnuksen asetelmissa ja kummallakin suoriutumisindikaattorilla testattuna. Hypotetisoitujen mediaatiovaikutusten osalta tutkimus ei löytänyt tilastollisesti yksiselitteistä näyttöä sille, että esimerkiksi aineettoman pääoman tekijät toimivat mediaattoreina tietojohtamisen käytäntöjen vaikutuksille suhteessa organisatoriseen suoriutumiseen. Koska viitteitä kausaalivaikutuksista kuitenkin esiintyi, esitetään jatkossa suoritettavaksi lisätutkimuksia perimmäisten ja mahdollisesti piilevinä esiintyvien rakennemuuttujien välisten kausaaliriippuvuuksien osoittamiseksi. Lisäksi osana loppupäätelmiä suositettiin, että nyt tehtyjä tarkasteluja täydennetään lisämallinnuksin ja aineistokäsittelyin mahdollisten mediaatiovaikutusten osoittamiseksi tietojohtamisen käytäntöjen, aineettoman pääoman eri osatekijöiden ja organisatorisen suoriutumisen välillä, missä voidaan hyödyntää sekä tietoa indikaattorimuuttujista että tässä tutkimuksessa tehtyjä havaintoja.

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About a year ago, while I was attending in the lectures of the course “Strategic Management of Intellectual Capital”, I became impressed by the knowledge-based view and its resource-based foundations that also form a basis for the theorisations on intellectual capital. Then I also began to develop ideas on my thesis topic and thought that it could be linked to modelling and theories on the value creation and knowledge management of companies, for instance. Luckily there were already data available and collected by the project “Intellectual capital and value creation” for different modelling purposes. Based on these ingredients and after consulting my supervisors, I was finally capable to compile a plan for the study, the steps and results of which are documented on the pages of this thesis.

Above all, I would like to thank Professor Aino Kianto who was my first supervisor and provided her continuing and firm support in all stages of this study. As a coordinator of the abovementioned project, she also allowed me to utilise the data collected during its earlier implementation. I also wish to thank Doctor Mika Vanhala who was my second supervisor and provided valuable comments on this study. Mr. Henri Inkinen also supported me in data processing related procedures. Thanks are also due to the Finnish Patent and registration Office and the Deputy Director General Olli Koikkalainen, especially, for permission to utilise the financial database of Virre in compiling supplementary financial information needed for this study.

I dedicate this thesis work to my wife, Mari, and to my sons, Aukusti and Verneri, who have patiently supported and encouraged me during my studies that I conducted at the Lappeenranta University of Technology during the past 15 months. This is the least I can do, even though I am completely aware that this thesis and my statement cannot recover the moments lost due to this intensive study period that is now coming to its end.

Joensuu, November 28, 2015

Kalle Eerikäinen

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SYMBOLS AND ABBREVIATIONS

DCV	Dynamic capabilities view
D-G's ρ	Dillon-Goldstein's rho index
GDP	Gross-domestic product
HRM	Human resource management
H1–H3b	Hypotheses *H1*, *H2*, *H3a* and *H3b*
IC	Intellectual Capital
IC&VC	the Intellectual Capital and Value Creation project
ICT	Information and communication technologies
KBV	Knowledge-based view
KIFs	Knowledge-intensive firms
KM	Knowledge Management
LISREL	Linear structural relations
n	Number of observations
$N_{\text{employees}}$	Number of employees
OP	Organisational Performance
p	*p*-value used for determining significance of statistical results obtained
pathdiagram	An accessory package of R for drawing path diagrams in PLS-PM
PLS	Partial Least Squares
plspm	A package of R software for the estimation of parameters of PLS path models
PLS-PM	Partial Least Squares Path Modelling
qqnorm	A function of R software for producing the Normal Q-Q plots
Q^2	Stone-Geisser's Q^2 index
R	A free, open-source and cooperatively developed software implemented with the statistical programming language and computing environment of the S software
R^2	coefficient of determination
RBV	Resource-based view
ROA	Return on total assets
ROE	Return on equity

RQ	Research question
S	A commercial software with statistical programming language and computing environment
sem	A package of R software for the estimation of parameters of PLS path models
SEM	Structural Equation Modelling
semPLS	A package of R software for the estimation of parameters of PLS path models
shapiro.test	A function of R software for the Shapiro-Wilk normality test
t	A test statistic, i.e. *t*-value, following a Student's *t* distribution
TOL2008	Finland’s national Standard Industrial Classification

1 INTRODUCTION

1.1 Background

The importance of physical capital factors as critical assets in the wealth creating process for firms and other organisations has diminished, whereas the magnitude of intangible forms of capital, i.e. knowledge, relationships and technological arrangements that contribute to the reputation, brand, corporate image, immaterial property rights, stakeholder relationships and information systems, for instance, has strengthened as the factor critical to their value creation dynamics (e.g., Lönnqvist et al., 2009; Isaac et al., 2010; Lerro et al., 2014). The interest by the strategic management discipline towards to the utilisation of intangible resources and development of knowledge-related management practices and production processes has been constantly increasing because of their potential to improve organisational performance along with the processes of value creation and, therefor, to provide companies with competence needed in creating a sustainable competitive advantage (see Grant, 1996; Spender et al., 2013).

Among the theories of the firm, the abovementioned knowledge-related aspects are traditionally analysed from the perspectives of the knowledge-based view (KBV) (Grant, 1996) that originates, especially, from the resource-based view (RBV) of the strategic management (e.g., Barney, 1991). In the knowledge-based view not only the knowledge-related resources, i.e. intellectual capital (IC) assets, but also organisational learning, management of technologies and managerial cognition are strategically motivated and emphasised (Grant, 1996; see also Kianto et al., 2014). When discussing about the RBV and KBV, it is also worth remembering that there also exists a third view, i.e. the dynamic capabilities view (DCV) of strategy by Teece et al. (1997), related to other two and contributing this field of research on management and organising (cf., Eisenhardt & Santos, 2006).

Intangible, knowledge-related resources governed by the organisation generate the stock of its IC, and they also form the key resources for the knowledge management (KM) of the organisation (e.g., Molodchik et al., 2014). Johannessen et al. (2005) define the IC as an expression used in denoting all immaterial resources that facilitate value creation and are essential for accomplishing the goals and competitive positioning. The IC is often itemised by the asset subcategories of the human (e.g., skills, experiences, abilities and motivation), structural (or organisational; e.g., organisational routines, procedures, processes, systems and cultures, and databases and patents) and relational (e.g., relationships and links with customers, suppliers, research and development partners and stakeholders, and brand image, customers' loyalty and satisfaction, agreements, environmental activities, etc.) capital (e.g., Bontis, 2001; Meritum Project, 2001; Marr, 2006; Isaac et al., 2010; Mention & Bontis, 2013; Bornemann & Wiedenhofer, 2014; Kianto et al., 2014; Inkinen, 2015). The objective of KM, on the contrary, is to leverage the existing knowledge and create new knowledge for positioning against competition and by focusing on the development of company's capability to control and manage its knowledge-related infrastructure and processes (Gold et al., 2001).

The relationship between the intangibles of IC assets and the KM practices can also be explained by the IC metrics and information based on them that provide the managers with knowledge-based navigators needed in capturing, positioning, directing and speeding organisational activities, where the role of KM is to utilise the information in guiding the dynamic process of value creation (Edvinsson, 2013; Molodchik et al., 2014). It is also in this respect that the interest towards intangible assets and their management and valuation lead to the establishment of the "Swedish Community of Practice" in early 1980's, the designs and concepts of which were further developed from the practical perspectives in Swedish companies followed by their counterparts in northern America (see Sveiby, 1997). At Scandia AFS – a pioneering company in the systematic utilisation of IC-based assets – this progress started in early 1990's as described by Edvinsson (1997). The origins of the concept developed by the Community can be traced to the well-known and widely applied balanced scorecard approach (see Johannesse et al., 2005).

The evident contribution of both IC and KM to the organisational performance has been extensively studied during the last decades, but it is still likely that the empirical evidence on the impacts of IC, for instance, has remained scarce in certain sectors and geographical regions as it was recently stated by Mention and Bontis (2013). However, instead of continuing to analyse the effects of IC assets and the KM processes and practices on the organisational performance (OP) separately, there is a need for research to be conducted for increasing understanding of the dynamics and processual nature of the value creation by analysing the dependencies and impacts of IC- and KM-related variables simultaneously. These needs for further research were recently addressed and theoretically justified by Kianto et al. (2014).

It is important to note that increasing the current understanding and knowledge on the interactions between IC and KM and their impacts on OP is not only of interest from the scientific perspectives. It is also expected that by using empirical data containing different items of KM and IC for the verification that the assumed interactions between these predictors are affecting OP positively would guide the practitioners in their management work of companies. Then, for instance, the IC management of companies could utilise more comprehensively the potentials of KM processes in the development of the strategic planning, management and implementation activities related to the acquisition and growth of intangibles (see Marr et al., 2003; Kujansivu, 2008). It is therefore worth assuming that by increasing understanding about the interaction between the tactically oriented and at the operational level influencing procedures of KM and mainly strategically focused management of IC assets would reflect to the performance of companies by improving their value-creation capacity (cf. Wiig, 1997; Zhou & Fink, 2003; Kujansivu, 2008; Kianto et al. 2010).

Assessing the impacts of KM and IC on OP by using concrete indicators available from the lines of companies' financial statements, would also extend the practical applicability of the results by providing managers with metrics to be used as a basis to elaborate their monitoring and reporting procedures on IC (cf. Mention & Bontis, 2013). This field of research is therefore of actual relevance when considering that companies are becoming increasingly dependent on KM-related practices needed for obtaining, growing and sustaining their IC; the KM practices and IC assets can be regarded as central sources of competitive advantage of the companies struggling in the complex knowledge-based economy of today (e.g., Marr et al., 2003).

The new data containing information on the indicators of IC assets, KM practices and OP factors measured by the sample units, i.e. the Finnish companies, were concrete enablers of this study. They were also needed for verifying the earlier assumptions and for testing the hypotheses on the interactions between the IC and KM affecting the OP of the company in a positive way. In this study, empirical data comprising several items measured by IC, KM and OP attributes together with structural path modelling formed a basis to extend our knowledge on the management of IC and its impacts on the value creation in the case of Finnish companies.

1.2 Objectives and research questions of the study

In IC research, it is traditionally hypothesised that there exists a positive dependency between the variables characterising the IC assets and OP (e.g., Mention & Bontis, 2013; Inkinen, 2015), a relationship also analysed and discussed in the recent studies including those by Bornemann and Wiedenhofer (2014), Massaro et al. (2015), Nimtrakoon (2015), for instance. The existing academic literature also provides evidence on the multidimensionality of the IC and the summation of its separable but strongly intertwined asset types positively impacting OP (cf., Isaac et al., 2010; Mention & Bontis, 2013; Massaro et al., 2015).

The importance of KM as a success factor of organisations is constantly increasing not only among the knowledge-intensive firms (KIFs) (see e.g., Alvesson, 2004) but also in the case of business companies from different fields of industries (see e.g., Hussi, 2004). There are also numerous studies available including those by Gold et al. (2001), Lee and Choi (2003), Chourides et al. (2003), Chuang (2004), Darroch (2005), Andreeva & Kianto (2012), Lee et al. (2012), Massingham & Massingham (2014), just to name a few of those reporting the positive effects of different KM practices and their related processes and enablers on OP.

The interactions of the IC assets and KM practices and their combined effects in relation to OP was recently theorised and discussed by Kianto et al. (2014). The theorised findings by Kianto et al. (2014) about the interlinked and positive effects of the IC assets and KM practices with their static and dynamic natures, respectively, on the organisation's value creation formed a basis for their simultaneous utilisation in the structural modelling of OP in the case Finnish companies. One interesting starting point for the model-based analyses of these causalities was to examine the so-called mediation effects as suggested by Kianto et al. (2014). With respect to the characteristics assessed and analysed in this study, not only the interaction between IC and KM but also the indirect effects between KM and OP and IC and OP mediated by IC and KM, respectively, was therefore of special interest (cf. Kianto et al., 2014).

In their study, Kianto et al. (2014) also suggested that objective indicator data from financial databases for measuring and assessing OP would be required for eliminating the common method bias which can affect the results obtained using survey-derived performance data. Besides their objectivity, the different measures available from financial information databases for indicating OP also strengthen the dynamic features of the data needed for analysing causal effects associated to the relationships between variables, the factor central to this study as discussed above (e.g., Tanriverdi & Venkatraman, 2005; Kianto et al., 2014).

Based on the earlier findings and discussions on the aspects of IC assets, KM practices and OP, it was possible to formulate the objectives and research questions for this thesis study. The general objective of this research was to contribute the current knowledge-based theory by focusing on a research gap that exists in the empirically proven determination of the simultaneous but differentiable effects of IC assets and KM practices positively impacting OP.

The analysis built on the past research utilised a structural path modelling technique in investigating the relationships between and the effects caused by the variables mentioned and introduced above, i.e. IC, KM and OP. With the aid of the structural path modelling-based analysis and by utilising empirical data gathered from a sample of Finnish companies the study aimed to find answers to the three central research questions (RQ) stated as follows:

RQ1: Are the theoretically assumed causal effects of IC assets and KM practices positively impacting OP also empirically proven?

RQ2: How appropriate is the structural path modelling-based analysis for assessing the interactions between the constructs of KM, IC and OP using a multisource data with different scales?

RQ3: How suitable are the measures obtained from the financial databases to determine OP?

The objective of the first RQ was to find empirical support for the hypothesised mediation effects for the dependences between KM, IC and OP, especially. This was conducted in relation to the verification of earlier reported significant dependencies between the components of IC and OP or KM and OP. In the model-based testing approach conducted, the aim was thus to establish a modelling setup by combining the theoretical framework derived from the existing scientific literature with a statistical multivariate modelling tool appropriate for analysing simultaneous effects between variables determined from empirical data. The empirical modelling data comprised both survey-based measures on KM and IC and financial information needed for determining indicator variables for OP. These data were collected by a sample of companies obtained from Finland only. In addition, only the structural variable constructs for IC assets and KM practices combining the survey-data based indicators, respectively, were used in modelling the outcome variable, i.e. OP. Modelling the possible moderation effects in relation to IC, KM and OP was also excluded because they were deemed out of the scope of this study.

The objective of the second RQ was to assess the suitability of the structural path modelling approach in relation to the analysis of effects between the modelled constructs of KM, IC and OP when using data gathered from different sources and containing measurements with different scales. Thus the new findings on the modelling approach in relation to the data used were assumed to assist the implementation of forthcoming studies, for instance.

The objective of the third RQ was to determine objective indicators for OP based on financial information available from the companies subject to this study. The selection of the financial performance indicators was based on the review of articles in which the results of model-based analyses conducted using financial measures as indicators for OP were reported. It was also of interest to analyse the magnitude and variation of these characteristics in the Finnish data and to make comparisons to the findings on the same indicators reported in the earlier studies. Thus obtaining a more solid basis of data for this and forthcoming studies to be conducted was also a pre-set target related to the RQ3.

1.3 Structure of the Thesis

The structure of this thesis at hand is specified with the aid of a process chart given in Figure 1. In chapter 1, an introduction to the research conducted on the strategic management discipline in relation to the intangible resources and knowledge-related management practices and processes associated with the organisational performance is given. In addition, the study objectives and research objectives are specified in the first chapter of the thesis.

The focus of the second chapter is in the evaluation of concepts and theories behind the KM practices and IC assets. These factors are thereafter assessed in the light of the value creation of companies. Finally the concepts on KM and IC are elaborated for forming the framework of the study in which the empirical data with structural path modelling is utilised in testing the hypotheses of the study.

In the third chapter, the procedures related to the collection of empirical data are described followed by the specification of items measured by the independent model constructs and derivation of dependent performance variable construct. The characterisation of study data is supported with the tabulated summary statistics by the variables modelled and control variables obtained by the companies belonging to the sample. Finally, the estimator used in the estimation of the values of parameters of the structural path models is introduced.

The fourth chapter of the thesis presents the results of the study with respect to the analysis of data, structural path modelling, general validation of structural path models obtained and significance tests conducted by the parameters of models. The results obtained by the structural models and their parameters are finally utilised in the assessment and validation of the hypotheses set in the second chapter.

The fifth chapter is finally received for evaluating the results and findings in relation to the theoretical background. The importance with respect to the model-based research in the fields of KM and IC is also elaborated and discussed. In addition, limitations related to the assessment of results and their generalisation and the needs for further investigations are discussed in this chapter.

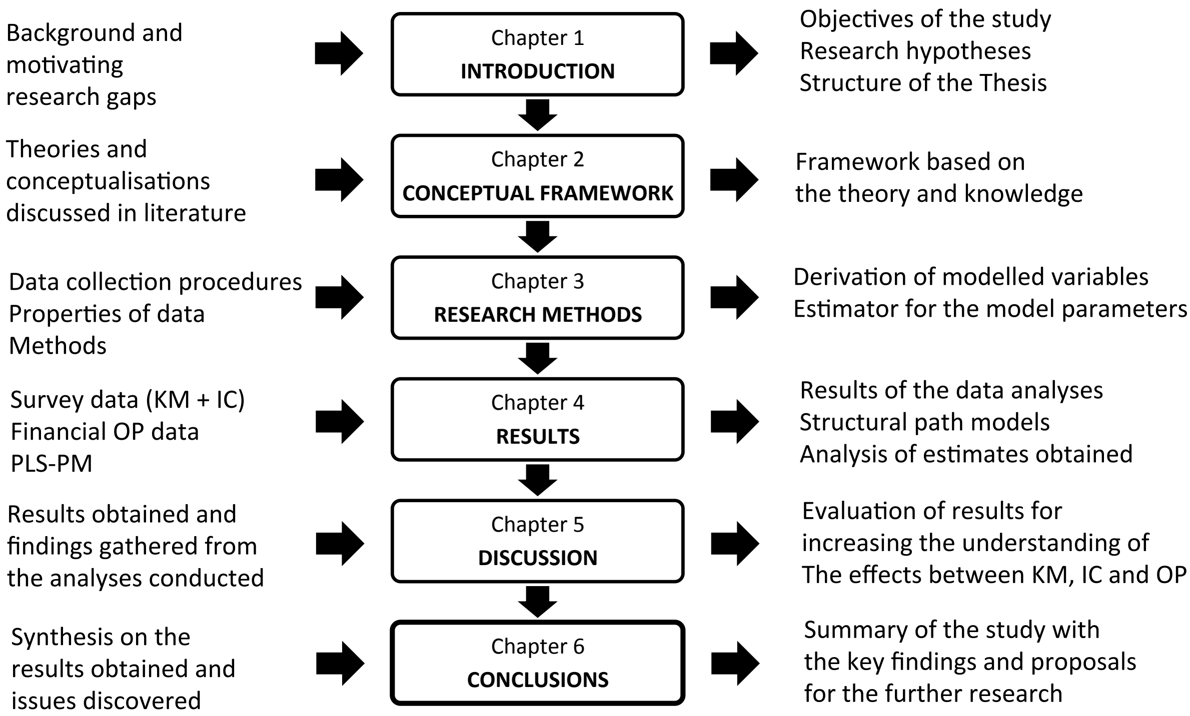

Figure 1. Flowchart structurising the outline of the study.

In the sixth chapter, conclusive statements for the study are given. In this last chapter before the list of references utilized in the study, the central results and key findings together with the proposals of further studies are presented in a condensed form.

2 CONCEPTUAL FRAMEWORK

2.1 Defining IC assets and KM practices

The IC held by an organisation can be understood to consist of various intangible factors related to firm competitiveness, business processes, functions on customer relationship management, and external and internal relationships, for instance (cf. Kujansivu, 2008). Even if IC forms a multidimensional concept, it is generally acknowledged to comprise different asset types related to human, structural and relational resources of the firm, which are strongly intertwined (e.g., Meritum Project, 2001; Marr, 2006; Mention & Bontis, 2013). IC and the organisational capabilities based on knowledge can be undoubtedly regarded as belonging amongst the most critical resources for today's companies operating in an increasingly competitive and risky environment and also including knowledge-intensive firms (cf. Marr et al., 2004; Marr, 2006; Kujansivu, 2008; Mention & Bontis, 2013).

An organisation excels, essentially, in terms of its core competencies comprising different capabilities that result from activities conducted both at individual-level and organizational-level (see, Prahalad & Hamel, 1990; Marr et al., 2004). At the individual-level, in particular, personal knowledge, individual skills and talents are the key sources of competence, whereas at the organisational-level infrastructure, networking relationships, technologies, routines, trade secrets, procedures, and even organisational culture are among the creators of competence acknowledged (Marr et al., 2004).

The understanding of knowledge has widened and it is nowadays understood to comprise both *i*) the explicit results of knowledge-intensive work that includes, for instance, patents, formulae and actualised products, and *ii*) the tacit capability potentials of organisational actors that materialise in flexible and timely reactions to unexpected situations and customers' changing demands and expectations (see Kianto et al. 2014). Resulting from the diversified content of knowledge, the definition of IC has also extended to cover not only the aforementioned and traditionally named components, i.e. human, structural and relational capital assets (e.g., Meritum Project, 2001), but also the extensively emphasised dimensions of *i*) renewal capital comprising resource type of enablers needed for organisational growth and long-term research and development (see Bontis, 2004; Kianto et al., 2010), *ii*) trust capital originating form the trust embedded in internal and external relationships and materialising in their interactive behaviours and processes (e.g. Mayer et al., 1995); and *iii*) entrepreneurial capital actualising in the organisational competence and commitment in entrepreneurially-related activities (e.g. Erikson, 2002). (See Kianto et al., 2014; cf. Isaac et al., 2010).

In KM, according to Marr et al. (2003), it is a question of a group of processes and practices applied by organisations, the objective of which is to increase the value of these operational entities by enhancing the effectiveness of their capacity to generate and apply intellectual capital assets held by them. Marr et al. (2003) discuss further about the nature of KM processes and explain that they should be regarded as meta-processes different from physical processes that differ according to their creation, means, recording, transmission and using mode and can be uniformly observed unlike their meta type of counterparts (see Marr et al., 2003). Marr et al. (2003) also suggest that the KM implementations vary between organisations because of the differences observable in their socio-cultural contexts and due to the fact that human beings, i.e. the KM applicators and developers, have different perceptions and principles of philosophies. Even if the categorisation of KM practices is less established when compared to that of the IC assets, they are identified in the literature as the tools organisations apply to leverage their IC assets and are often related to the strategic management, organisational restructuring, organisational culture influencing knowledge creation and sharing behaviours, management features and systems based on information and communication technologies (ICT), learning mechanisms, knowledge-focused human resource management (HRM), and knowledge protection, as it was recently discussed by Kianto et al. (2014).

The differences between the IC assets, i.e. knowledge resource stocks, and KM practices was also recently scrutinised by Kianto et al. (2014), who analysed the IC assets and KM practices with respect to their static and dynamic natures. The static nature of the IC assets reflects to the capital type of knowledge viewed at the given point of time that is available for but not necessarily exploitable by the organisation in its value creation. In the dynamic perspective of IC, the temporal nature of the analysis, in which it is practically taken dealt with that the organisation possesses in terms of its IC assets at the given time, is leveraged to that what the operation actually does for managing those assets. It is therefore possible to summarise that the functional nature of the intangible resources controlled by an organisation is two-fold, i.e. they: 1) establish – in the form of IC assets – a key potential for the value creation, and 2) comprise the means, i.e. KM practices, needed for controlling and managing the former. (See Kianto et al., 2014.) The dynamic nature of the abovementioned KM practices can be argued, on the contrary, based on the management that triggers the motion of static assets that in turn provides the management with the dynamism that catalyses it for the further value creation (see Kianto et al., 2014). The latter mentioned forms a central aspect of this study and is a statement that refers to the discussion on the theory of entrepreneurship by Schumpeter (1983).

2.2 IC assets and KM practices in relation to management and value creation

In his article on the development of knowledge strategy of the firm, Zack (1999) emphasised knowledge as the firm's most important strategic resource. He also stated that firms having superior intellectual resources are also holding a better capacity to exploit and develop their actual resources and provide more value to the customers compared to their competitors. The statements by Zack (1999) form a continuation of the earlier discussions by Barney (1991) and Grant (1996) on the RBV and KBV of the firm, respectively. An interesting and partly opposing perspective to the strategic role of knowledge was given by Eisenhardt and Santos (2006) who analysed the phenomenon in relation to the value creation of the firm and, especially, to its conceptualisation as a firm's acquirable, transferrable, and integreteable resource. They argued that the strategic logic of KBV should be generally seen as an extension of the RBV of strategy and that it should, in fact, be regarded as an approach based on the DCV by Teece et al. (1997) (Eisenhardt & Santos, 2006; see also Eisenhardt & Martin, 2000).

The statement by Mention and Bontins (2013) on the central role of the IC assests as the most critical resources for KIFs is indisputable. By Alvesson (2004), the KM practices are deemed more significant for KIFs than other organisations; KM practices are defined to essentially include activities conducted to improve the use of knowledge by building upon the existing knowledge and to stimulate innovativeness through different combinations of competences. Because the logic of business is extensively transferring from massproduction to knowledge-intensiveness, the progression does not only apply to modern industries related to ICT sector but also to the forest industry as an example of the more traditional ones (Hussi, 2004). Therefore, the theoretical concepts of IC, intangible assets, knowledge creation and KM are needed to tackle this timely issue challenging the companies in general (Hussi, 2004).

According to Marr et al. (2003), the successful management of IC is closely linked to the KM processes an organisation is applying and which, in turn, supports the implementation and usage of KM needed to ensure the provision and extension of IC-based assets. They define the KM as a pooled group of processes and practices that contribute to the organisation's value creation, even if the meta-process type of KM processes – unlike their physical counterparts – are unobservable and differ in terms of their establishment, character, transmission, mode of use etc. (See Marr et al., 2003).

In the management of IC, different operational procedures are conducted, and according to Marr et al. (2003, 2004) they can be comprised as follows: 1) identification of key drivers of IC influencing the strategic performance of the given organisation; 2) visualisation of the key IC assets with respect to their value creation pathways and transformations; 3) measurement of performance and dynamic transformations, especially; 4) cultivation of the key IC assets by utilising KM processes; and 5) compilation of reports on the performance for internal and external reporting purposes. Due to the differences between the KM processes and due to their socio-cultural dependency (Marr et al., 2003), for instance, it is logical to assume that the IC management implementations are organisation-specific, at least to some extent. The differences between organisations are also emphasised by Kujansivu (2008), who sees that operationalising IC is a case-procedure to be adopted from the strategic perspectives of the company.

The differences between KM and IC management can also be inspected from the perspectives of management and organising. Wiig (1997), for instance, emphasizes that KM is a more detailed approach with focus in the facilitation and management of knowledge-related activities. Therefore, its perspectives are mainly tactical and operational (see Wiig, 1997). In the management of IC, on the contrary, the focus is on the strategic-level managing and operating procedures used in building and governing intellectual capital assets that are also impacted by and connected to the external environment of the organization, i.e. customer relationships, business processes etc. (Wiig, 1997; Kujansivu, 2008). Thus the function of the IC management is to take holistic care of the company's IC assets (Kujansivu, 2008).

As it was discussed by Hussi (2004), the business rationale of intellectual capital, on the contrary, can be explained by the generative intangible assets, which form a modifiable input for the dynamic process of knowledge creation (see Nonaka et al., 2000) and for the static resources that after being combined into dynamic process create a basis for the future success of the company in the forms of commercially exploitable intangible assets, i.e. resulting outputs of the process. In addition, the knowledge vision – a tool articulated and communicated by the top management for synchronising the entire organisation – is the driving force of activities related to KM and forms a basis for the company's generative intangible assets (see Hussi, 2004). Therefore, the knowledge vision-based definition for the relationship between the IC and KM is at least to some extent parallel to the discussion on the organisational culture and leadership promoted by Schein (2010).

2.3 Simultaneous effects of IC assets and KM practices on the organisational performance

Understanding and itemising the knowledge-related factors as creators of the competitive advantage of company and as organisational capabilities needed in maintaining and growing this advantage is central to a successful execution of strategy (Marr et al., 2004). Thus the development of IC and its different asset categories which form the foundation of organisational capabilities can be regarded as an approach and evolving discipline essential in improving the performance of companies (see Marr et al. 2004).

As it was recently discussed by Kianto et al. (2014), there seems to be only few if any studies conducted to analyse the dynamics and interactions of the KM practices and the IC assets in relation to the value creation of companies. The number of studies examining either the effects of IC assets on OP or the KM practices on OP is, however, quite substantial and has increased by many recent references (e.g., Andreeva & Kianto, 2012; Lee et al., 2012; Mentions and Bontis, 2013; Bornemann and Wiedenhofer, 2014;

Massingham & Massingham, 2014; Massaro et al., 2015; Nimtrakoon, 2015). In addition, the different structural modelling approaches have been already applied in analysing interactions between the IC assets and their enablers (Isaac et al., 2010), impacts of IC assets on OP (e.g., Mentions and Bontis, 2013; Massaro et al., 2015), effects of KM-based infrastructure and process capabilities on organisational effectiveness (Gold et al., 2001), and relationship between KM-practices, innovation and firm performance (Darroch, 2005), for instance. These studies including, especially, the one by Kianto et al. (2014) provided starting points for the further, synthetised studies on modelling the knowledge-related value creation features of companies based on empirical data.

With respect to the model building objectives of this study, the term OP was defined as an outcome variable, i.e. dependent variable construct, that was obtained using financial performance measures. OP was thereafter predicted as a function of independent variables obtained using capital asset indicators for constructing a component for IC and different management practice indicators for constructing a component for KM (see chapters 2.1 and 3.1.1). Generally, the dependent variable construct of the structural path model determining OP can comprise appraisal measures obtained from questionnaires and objective financial outcome measures derived from financial statements of companies (cf. e.g., Hair et al., 2010). It is worth to noting that “value creation” should be seen in this context as a meta-level concept discussing the process as a whole. (See e.g., Mention & Bontis, 2013; Kianto et al., 2014).

Multivariate modelling allows the analyst to model causal relationships among variables in process systems, such as the company’s value creation, in the light of theoretically sound and empirically justifiable relations and dependencies that can be interpreted and specified by introducing the distinctive patterns of mediating and moderating relationships (e.g., Spicer, 2005; Cooper & Schindler, 2008; Hair et al., 2010). There also exists a so called “confounding pattern” that is, however, associated to the distorted individual effects of independent variables that are related among themselves on dependent variable(s), an event tackleable by the means of statistical control used to obtain unconfounded effects on the dependent variable(s) (e.g., Spicer, 2005).

The moderation pattern opens up the way for theorising the relationships between variables, and in the simplest hypothetical case it exists between three variables (e.g., two independent variables and one dependent variable such as constructs for IC and KM, and OP, respectively). Then it is suggested that the relationship between one independent and the dependent variable is moderated by another independent variable, i.e. the relationship between the two variables differs according to the level or amount of the third variable, i.e. moderator. In the case of mediating pattern, on the contrary, the causal chains are of interest in theorising the between-variable relationships. With the two imagined independent variables and their dependent counterpart, its possible to define this pattern by the causal chain linking of the three variables: the second variable (independent) in the middle mediates the effect of the first variable (independent) on the third variable (dependent). This means that the effect of one independent variable on the dependent variable fluctuates through another independent variable that is an explicit example of indirect effects. In Figure 2 and in the case of model 5 in Figure 3, especially, it is hypothesised that the independent variable, i.e. latent variable construct, “IC” is intervening the indirect effect of another independent variable “KM” on the dependent variable “OP”. It is thus assumed that the construct IC is acting as a mediator of the relationship between the constructs of KM and OP (cf. the direct effect between the constructs of KM and OP is also specified with an arrow in the structural path model of Figure 2). (See e.g., Spicer, 2005; Hair et al., 2010).

The theoretical examinations conducted by Kianto et al. (2014) on the IC assets and KM practices and their combined effects on the OP provided interesting and logical insights to the mechanisms of value-creation which helped to structurise the phenomenon of interest in the form of structural path model. Their interpretations on the static and dynamic aspects of organisational knowledge-based value creation and suggestions on the specification of between-variable relationships based on the conceptualisation of pattern models for moderation and mediation in the context of KBV. Their study also provided theoretically sound starting points for empirical testing and verification of assumptions on the interactions between the static IC assets and dynamic KM practices and their simultaneous effects on the OP using the data available for this study.

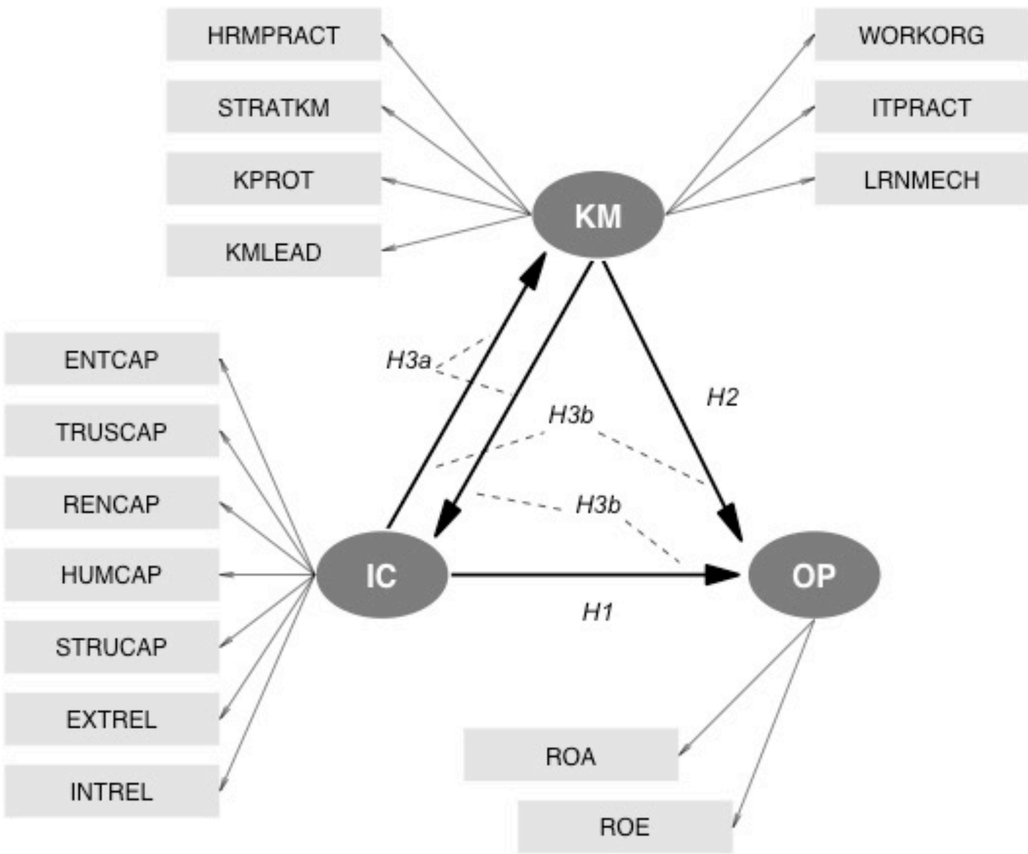

Figure 2. A conceptual research model of direct and indirect effects hypothesised in relation to the modelled path model constructs for KM, IC and OP and their sub-categories. Sub-categories for IC are as follows: 1) internal cooperation relationships (INTREL), 2) external cooperation relationships (EXTREL), 3) internal structures (STRUCAP), 4) employee competence (HUMCAP), 5) renewal capability (RENCAP), 6) trust (TRUSCAP), and 7) entrepreneurial orientation (ENTCAP). Sub-categories for KM are as follows: 1) supervisory work (KMLEAD), 2) knowledge protection (KPROT), 3) strategic knowledge and competence management (STRATKM), 4) human resources management (HRMPRACT), 5) learning practices (LRNMECH), 6) IT management (ITPRACT), and 7) work organisation (WORKORG). ROA and ROE for IC refer to financial performance measures, i.e. return on total assets and return on equity, respectively.

2.4 Hypotheses of the study

Due to the evidence provided about the positive impacts of IC on OP, it was also expected to be possible to analyse the phenomenon in relation to data available from the Finnish companies (cf., Isaac et al., 2010; Mention & Bontis, 2013; Massaro et al., 2015; Inkinen, 2015). It was also assumed that modelling of the dependence between IC on OP by using structural constructs comprising information on different categories of intangibles would provide new insights needed for understanding and interpreting the causal chains among and relationships between the components of IC affecting the dynamics of their value creation processes of the Finnish companies and materialising in their operations at the strategic-level (cf. Wiig, 1997). As a result, the following hypothesis related to the effects of IC on OP was formulated:

- *H1*: The interlinked IC assets are positively affecting OP.

Due to the increasing importance of KM for organisations and companies operating in different fields of industries (see e.g., Alvesson, 2004; Hussi, 2004) and because of the earlier findings on the positive effects of KM on OP, it was justified to expect that the positive correlation between the KM and OP also exists in the case of empirical data obtained from the Finnish companies (e.g., Gold et al., 2001; Lee and Choi, 2003; Chourides et al., 2003; Chuang, 2004; Darroch, 2005; Andreeva & Kianto, 2012; Lee et al., 2012; Massingham & Massingham, 2014). With respect to the earlier hypothesised relationships between the IC assets and OP, it was worth assuming that a more detailed, model-based analysis of the KM practices in the case of Finnish companies would provide new findings needed for explaining and verifying causalities related to their dynamic functionality in the process of value creation materialising in tactical operations and at operational level. Therefore, the following hypothesis related to the effects of KM on OP was formulated:

- *H2*: KM practices are interlinked and positively associated with OP.

The studies by Wiig (1997), Marr et al. (2003), and Kianto et al. (2014), for instance, are well-founded examples of discussions with an aim to increase our knowledge on the interactions of the IC assets and KM practices and their combined effects sustaining and improving the performance of companies and positively impacting their value creation. The theoretical models by Kianto et al. (2014) about the relationships between IC assets and KM practices with their static and dynamic natures, respectively, and about their causal relations impacting the performance of organisations formed a basis for their simultaneous utilisation in the structural modelling of OP in the case Finnish companies. Accordingly, the two hypotheses related to the interrelationships between of IC and KM impacting OP were formulated as follows:

- *H3a*: KM practices and IC assets are positively related; and
- *H3b*: dependency between KM practices and IC assets is causally related with positive impacts on OP.

As a summary of the variables modelled and sources of their items used in modelling (indicated by the sub-categories of KM, IC and OP), the research model for the study can be hereby illustrated according to Figure 2. As it can be seen from Figure 2, it is expected that there exist relationships between the predictors of OP and between KM and OP and IC and OP as defined in hypotheses *H1*, *H2*, *H3a* and *H3b* given above.

Therefore, the interactions relevant to different path model specifications can also consist both direct and indirect effects of KM and IC impacting OP. It is also worth noting that the two arrows indicating the effects between IC and KM and KM and IC with respect to hypothesis *H3b* are only used to specify that the either KM or IC can act as a mediator variable in relation to model-based analysis setup of this study. Thus the research model given in Figure 2 should be regarded as a general specifier for the different combinations of the dependencies modelled.

The validity of assumptions made on the interrelationships between the IC assets, KM practices and OP and specified by the hypotheses *H1–H3b* can be examined by utilising structural modelling techniques (see e.g., Hair et al., 2010). Based on the hypotheses above, a set of six structural path models for the constructs of KM, IC and OP was finally obtained as illustrated in Figure 3.

Using structural path models 1 and 2 defined in Figure 3, the direct effects of IC assets on OP (*H1*) and KM practices on OP (*H2*) were tested, respectively. With model 3, the direct effects of IC assets on OP (*H1*) and KM practices on OP (*H2*) were simultaneously tested, whereas not only the direct effects of KM practices on OP (*H2*) but also the indirect effects between KM and OP mediated by IC (*H3a* and *H3b*) were tested using model 4. Model 4 can also be called as a "full model" due to its complete path dependency structure specified between the constructs for KM, IC and OP. The models 5 and 6 were also obtained for testing whether the KM practices and IC assets are causally related with positive impacts on OP (*H3a* and *H3b*). When models 5 and 6 are compared to model 4, it is seen that they, unlike model 4, only tested and verified the differences of the effects between KM and OP mediated by IC (model 5) or the effects between IC and OP mediated by KM (model 6).

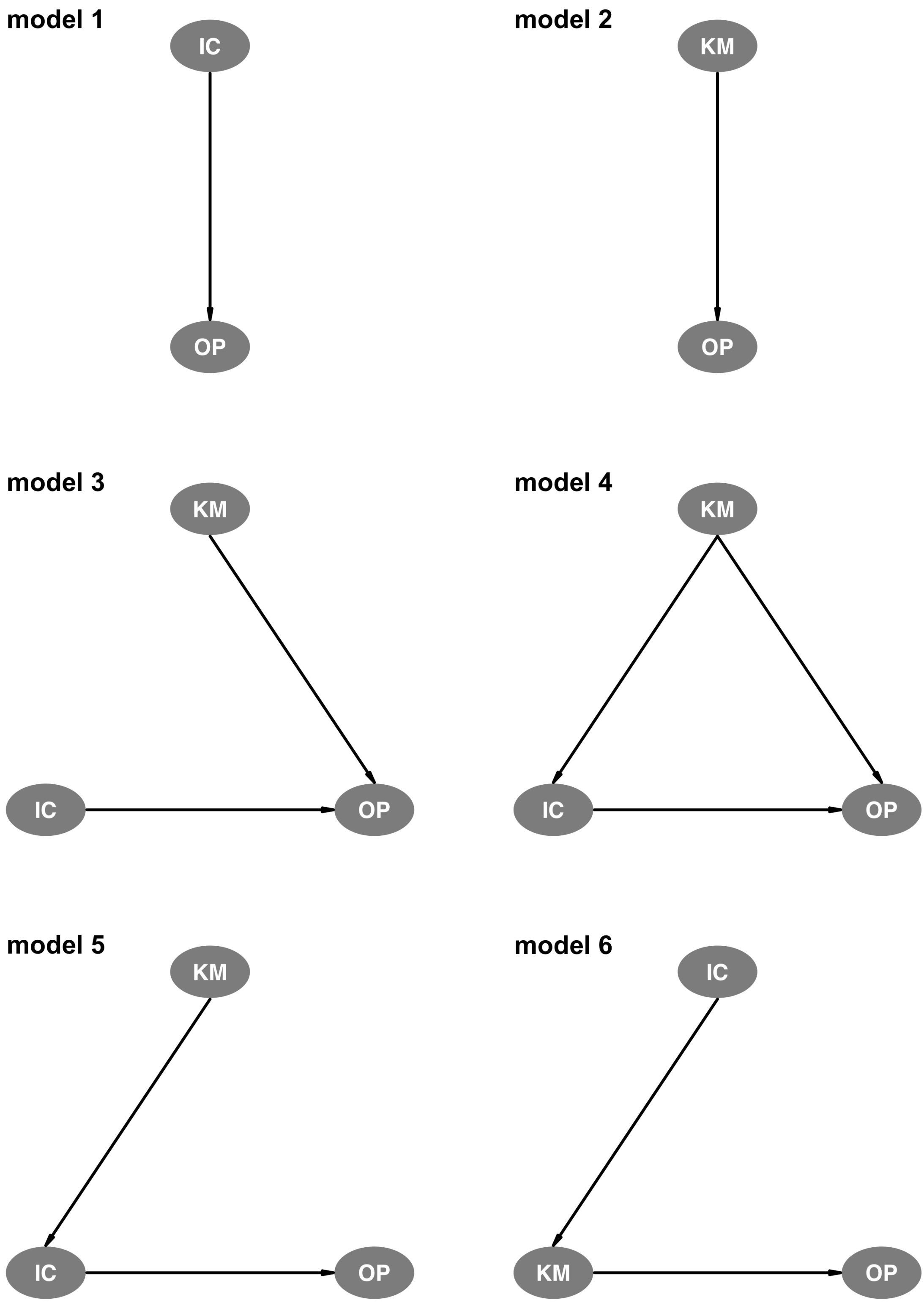

Figure 3. Illustration of the six path models specified for testing the hypotheses *H1–H3b* with different combinations of the constructs for KM, IC and OP.

3 RESEARCH METHODS

3.1 Study data

3.1.1 Items for the independent latent variable constructs

Modelling the effects of IC and KM on OP for testing the hypotheses was based on the survey data collected by the project entitled "the Intellectual Capital and Value Creation" (IC&VC) which was coordinated by the School of Business and Management at the Lappeenranta University of Technology. For computing objective measures of OP and determining control variables by companies, data available online in two separate financial databases were also utilised (see chapter 3.1.2).

The questionnaire developed by the IC&VC-project for collecting the survey data comprised a total of 91 items of which 28, 43 and 20 measured the indicator characteristics of IC, KM and OP, respectively. In addition, altogether nine questions on the respondent and company supplemented the information regarding the companies within the sample. The sampling frame of the survey covered all Finnish companies *i*) with 100 or more full-time employees, and *ii*) not registered in the region of Åland Islands. Technically, the procedures related to the sampling and resulting collection of the survey data by the sampled companies were conducted by MC-info Oy between September and November 2013. MC-info Oy (2015) is a marketing research and consulting company. The database provided by Intellia Oy (2015) was utilised in implementing the sampling. Intellia Oy (2015), on the contrary, is a service provider specialised in delivering information on companies and their customers needed for the sales, marketing and risk management of businesses. The items by the subcategories of IC, KM and OP and company characteristics together with the questions of the questionnaire used in collecting empirical data from the companies are listed in Appendix 1.

This study used a 5-point Likert-type scale to ask the respondent, who was supposed to be in the position of either a director or manager responsible for the human resource administration, to state to what extent he or she agreed or disagreed with the proposition given in the questionnaire. A total of 259 completed and valid surveys were collected during the data acquisition period from September to November 2013. Thus, the response rate of the survey was 17.2 %.

The questions related to IC-related resource assets were categorised into seven asset types as follows (cf. Appendix 1): 1) internal cooperation relationships (INTREL), 2) external cooperation relationships (EXTREL), 3) internal structures (STRUCAP), 4) employee competence (HUMCAP), 5) renewal capability (RENCAP), 6) trust (TRUSCAP), and 7) entrepreneurial orientation (ENTCAP). The questions on the KM, on the contrary, were categorised with respect to the seven types of practices as follows (cf. Appendix 1): 1) supervisory work (KMLEAD), 2) knowledge protection (KPROT), 3) strategic knowledge and competence management (STRATKM), 4) human resources management (HRMPRACT), 5) learning practices (LRNMECH), 6) IT management (ITPRACT), and 7) work organisation (WORKORG).

In terms of OP, the questions used in the questionnaire were categorised by the subject types as follows: 1) success in sales and marketing, 2) capacity to obtain innovations and new operating methods, 3) customer value creation, 4) effectiveness of innovation operations in terms of company's net sales, and 5) job satisfaction of employees. Instead of using the subjectively determined OP measures available in the survey data, i.e. the 20 items for OP in total, this study utilised objective measures in assessing the firm performance, also called as "financial performance measures" or "accounting-based performance measures" by Tanriverdi and Venkatraman (2005). Besides Tanriverdi and Venkatraman (2005), the financial measures – which can be deemed to be objective due to their countability – have been utilised in the modelling-based analyses on management research for determining the organisational performance, for instance, by Waddock and Graves (1997), Hillman and Keim (2001), Ray et al. (2013), Berry (2015), and Su and Tsang (2015).

3.1.2 Dependent performance variables of structural path models

The two widely used objective measures of performance recommended in the diversification literature as the dependent variables to test the validity of the hypothesised effects of KM and IC constructs on OP that were also used in this study are as follows:

- return on total assets (ROA) = profit or loss before taxes (€) / total assets (€); and
- return on equity (ROE) = profit or loss before taxes (€) / stockholders' equity (€).

ROA, which is generally defined to reflect company's efficiency in utilising its total assets, when holding its financing policy stable, was recommended and used as an objective OP measure by Waddock and Graves (1997), Hillman and Keim (2001), Tanriverdi and Venkatraman (2005), Ray et al. (2013), Berry (2015) and Su and Tsang (2015) (see also e.g., Castillo, 2003; Firer & Williams, 2003; Feng et al., 2004; Chen et al., 2005; Ting & Lean, 2009; Vidović, 2010; Clarke et al., 2011; Maditinos et al., 2011), for instance. ROE, which can be interpreted to represent the returns to shareholders of common stocks, and is generally considered as an important financial indicator for investors by reflecting the company's capacity to utilise its investment in terms of equity, was applied together with ROA in the studies by Waddock and Graves (1997), Hillman and Keim (2001), and Tanriverdi and Venkatraman (2005) (see also e.g., Castillo, 2003; Chen et al., 2005; Clarke et al., 2011; Maditinos et al., 2011).

In order to induce dynamic performance indicators into the modelling data, information available in the financial statements of 2014 for the companies subject to this study was utilised. Therefore a 1-year lag between the survey-based measurement of items by KM and IC conducted in 2013 and the collection of firm performance data for ROA and ROE from the financial data of 2014 was introduced, a procedure which corresponds to that applied by Tanriverdi and Venkatraman (2005), for instance. The main source of financial data and descriptive data (e.g., number of employees, industry, etc.) compiled by the companies was the Bureau van Dijk's Amadeus database that combines data from over 35 sources and provides the user with an online search engine software for collecting and analysing company specific data (Bureau van Dijk, 2015). The Amadeus database contains financial and business information in a standardised format from over 14 million companies across Europe.

Due to the differences in financial reporting procedures, the annual reports with financial statements were not, however, available in Amadeus by all the companies in the sample at the time of the collection of financial data for modelling. Therefore, the Virre database maintained by the Finnish Patent and Registration Office (2015) was used as a supplementary source of financial data needed for imputing missing variables when calculating performance characteristics of interest, i.e. ROA and ROE. If the information on ROA, ROE and descriptive characteristics of the certain company was not available from the Amadeus database, then the data for the given company (i.e., pre-tax income, value of total assets, value of equity, number of employees, class of industry etc.) were inquired from the Virre database providing an access to the completed financial statements of the Finnish companies.

Using information available in Amadeus, it was possible to obtain financial OP measures for altogether 217 companies (83.8%). From the completed financial statements stored into Virre database, variables needed for calculating the financial OP measures were extracted for 27 companies (10.4%). For the remaining 15 companies (5.8%) the needed financial data were available neither in Amadeus database nor in Virre database when they were last accessed on November 4th, 2015. However, it is worth considering that in the case of altogether 11 companies the value of equity in the financial statement of 2014 was negative resulting in inconsistent definitions of ROE. Therefore, ROE was not determined in the case of these 11 companies that also corresponds to the procedure applied in the value imputation of ROE used to compile data for the Amadeus database.

In the case of Amadeus, the extreme values of ROE, i.e. over 10.0 (i.e., > 1000 %) or less than -10.0 (i.e., < -1000 %), are also excluded from the vector for the variable, a procedure which was also applied in this study. Moreover, in the case of seven subcategories of KM construct and seven subcategories of IC construct there was a total of 17 rows in the data which contained bundles of items with no measured values, i.e. missing values only. When the data rows containing extreme values of ROE and bundles of items of subcategories or missing values obtained for the dependent variables ROA and ROE were excluded, the modelling datasets for ROA and ROE contained the totals of data rows 228 and 215, respectively, which correspond to the total numbers of companies with respect to these two datasets. In order to eliminate an unnecessary loss of information, the remaining and singly appearing missing values were, however, accepted in the preparation of data for path modelling.

The analysis of the frequency distributions of dependent variables by the two datasets showed that in the distribution of ROA there was one observation with the value of 1.562 that was exceptional when compared to other ROA values in the data (n = 228; see Figure 4a$_1$). When the data row with this value was excluded, the remaining 227 values of ROA in the final modelling data formed a close to symmetrical distribution with the mean and median of 0.051 and 0.041, respectively, and values ranging from -0.769 to 0.993 (see Table 1; see Figures 4a$_1$ and 4a$_2$).

The initial data for modelling the relationship between KM, IC and OP using ROE as a dependent performance measure (n = 215) also contained one data row with an extreme value (see Figure 4b$_1$). When the row of data with the value of -9.111 (= -911.1%) calculated for ROE was excluded, the lower tail of the frequency distribution obtained for the remaining values of ROE (n = 214) became almost equal when compared to the upper tail of the resulting size distribution. Therefore, a close to symmetrical distribution with the mean and median of 0.167 and 0.135, respectively, and values ranging from -3.836 to 3.628 was also obtained for the second dependent variable modelled in this study (see Table 1, and Figures 4b$_1$ and 4b$_2$).

Table 1. Summary statistics for the control variables in the modelling data for ROA (n = 227) and ROE (n = 214), respectively.

Variable	minimum	mean	median	maximum	standard deviation
ROA	-0.769	0.051	0.041	0.993	0.157
Age, years	3	29.802	22	118	26.050
Number of employees	14	494.300	202	12364	1096.850
ROE	-3.836	0.167	0.135	3.628	0.837
Age, years	3	29.794	22	118	26.254
Number of employees	14	502.369	204	12364	1125.815

The normality of the final distributions of the two performance characteristics was tested by inspecting the Normal Q-Q plots produced with the function ‘qqnorm’ of R data package for data analysis (R core team, 2015) and using its function ‘shapiro.test’ for Shapiro-Wilk normality test obtained with respect to the vectors of ROA (n = 227) and ROE (n = 214). It was observed that the distributions obtained for the two variables did not follow the normal distribution. Therefore, the second principle, especially, stated by

Mention and Bontis (2013, see also chapter 3.2) on the advantages of PLS holds true in the case of modelling data of this study.

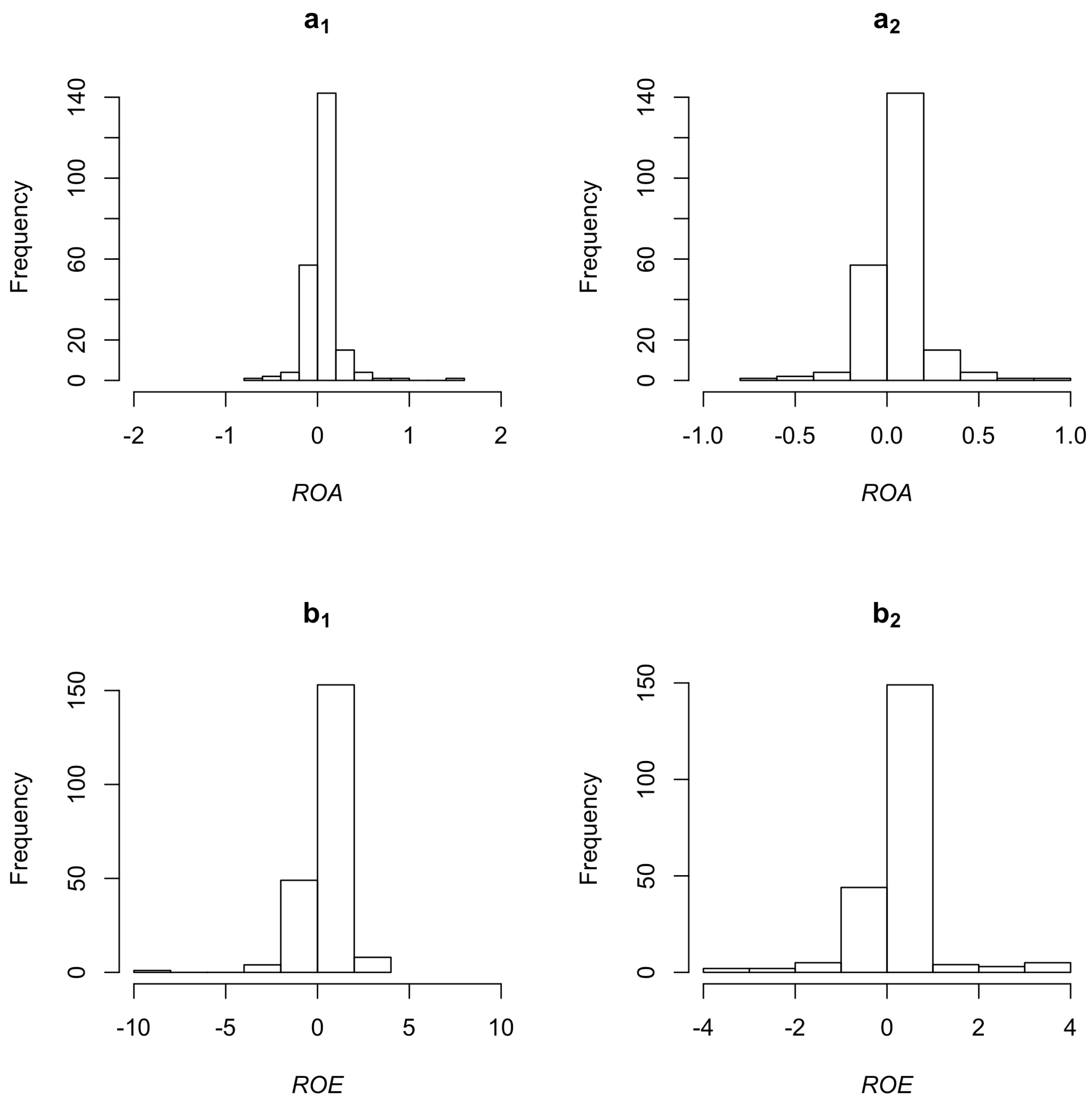

Figure 4. Histograms obtained for the vectors of ROA ($3a_1$ and $3a_2$) and ROE ($3b_1$ and $3b_2$) before ($3a_1$, $n = 228$; and $3b_1$, $n = 215$) and after ($3a_1$, $n = 227$; and $3b_1$, $n = 214$) the exclusion of exceptional values obtained for the two performance characteristics used in structural path modelling.

In spite of the difference of 13 OP observations (227 - 214 = 13) between the two modelling datasets, the summary statistics obtained for the control variables, i.e. age and number of employees of company, are very similar (see Tables 1 and 2). It is worth noting that the ranges of the two characteristics are equal and that approximately the same means, medians and standard deviations were obtained for the age of company and the number of employees in the two sets of modelling data (Table 1). The frequencies of observations were also categorised according to the Finland's national standard industry classification system, i.e. TOL2008 classification (Statistics Finland, 2015a). As it can be observed in Table 2, the differences between frequencies by the TOL2008 classes are also only minor when comparisons are made between the two modelling datasets (Table 2).

Table 2. Numbers (*n*) and percentages (%) of companies by the industry classes 1–8 of the Finland's national standard industry classification system, i.e. TOL2008 system, in the modelling data for the ROA (total sum = 227) and ROE (total sum = 214) -based analyses of OP.

	ROA		**ROE**	
TOL2008 class[*]	***n***	**%**	***n***	**%**
1	16	7.048	13	6.075
2	17	7.489	16	7.477
3	13	5.727	13	6.075
4	19	8.370	18	8.411
5	18	7.930	18	8.411
6	17	7.489	16	7.477
7	91	40.088	86	40.187
8	36	15.859	34	15.888
total sum	227	100.000	214	100.000

[*] TOL2008 classes: 1 = professional, scientific and technical activities, 2 = administrative and support service activities, 3 = information and communication, 4 = transportation and storage, 5 =services, 6 = construction, 7 = manufacturing, 8 = wholesale and retail trade, repair of motor vehicles and motorcycles.

In order to analyse the magnitude and variation of ROA and ROE in the modelling data of this study and for making comparisons to the findings on these OP characteristics reported in earlier studies, an additional literature review by inspecting articles on modelling studies and published in the management scientific literature was conducted. The estimated means and standard deviations reported for ROA (Studies I–VI) and ROE (Studies I–III) in altogether six well-founded scientific articles relevant and comparable to the modelling setup of this study are presented in Table 3.

It is possible to conclude that the mean and standard deviation obtained for the vector of values of ROA of this study (n = 227) are within the range of the two characteristics reported in earlier studies (see Table 3). When the same statistics obtained for the data vector of ROE of this study (n = 214) are inspected (see Table 1), it is observed that the mean is approximately from the same magnitude whereas the standard deviation is substantially higher when comparisons are made to their counterparts reported in earlier studies and listed in Table 3. In this study, however, no attempts were made to limit the variation of data by targeting the sampling into preselected categories of industries, for instance. On the other hand, the size variation of companies was only moderately restricted when carrying out the sampling, i.e. only companies having 100 or more employees were subject to sampling. These features related to the sampling procedure conducted can explain the larger deviation of ROE obtained for the Finnish companies of this study reported in Table 1 when compared to standard deviations of ROE given in Table 3.

Table 3. Sample sizes and means and standard deviations of economical performance measures (ROA and ROE) reported in studies I–VI by Waddock and Graves (1997), Hillman and Keim (2001), Tanriverdi and Venkatraman (2005), Ray et al. (2013), Berry (2015) and Su and Tsang (2015), respectively.

Variable	Characteristic	Study					
		I	II	III	IV	V	VI
Sample size	Number of firms	486	308	303	912	1801	2364
ROA	Mean	0.055	0.064	0.03	0.06	0.05	0.14
	Standard deviation	0.058	0.055	0.05	0.18	0.21	0.08
ROE	Mean	0.139	0.152	0.07	–	–	–
	Standard deviation	0.283	0.170	0.16	–	–	–

3.2 Testing hypotheses with structural path modelling

Among the various multivariate data analysis techniques available for the information exploitation and, especially, testing hypotheses, the structural equation modelling (SEM) and its sub-category, partial least squares-based path modelling, provide efficient approaches and procedures for the research targeted to increase understanding on the multiple interrelated dependence relationships, i.e. simultaneous direct and indirect causal effects between the independent and dependent variables (e.g., Cooper & Schindler, 2008; Hair et al., 2010; Mention and Bontis, 2013). Generally, the advantage of the structural modelling approaches is that they allow the researcher to examine these effects at the same time and to generate multiple combinations of the variables depending on the hypotheses to be tested (see e.g., Hair et al., 2010).

It can be also generally stated that in SEM, series of separate, interdependent multiple regression equations are estimated with the aid of the structural model specified by the modeller (see Hair et al. 2010). Due to their flexibility in terms of the technical model building and capability to simultaneously produce estimates even for multiple interrelated dependence parameters of related variables, the SEM techniques have been of increasing interest among the researchers modelling formative constructs in marketing, management and organisational research (see Monecke & Leisch, 2012). This also holds true for the current research on the IC- and KM-related modelling and interpretation of OP (e.g., Isaac et al., 2010; Mention & Bontis, 2013; Darroch, 2005).

In SEM, a researcher first determines and distinguishes based on the theory, prior experience and the pre-selected research objectives which of the independent variables predict each dependent variable; an dependent variable of one relationship can turn to independent variable in subsequent relationships leading to the fundamentally interdependent nature characterising all structural models. The task of the structural model is in fact to express and specify these dependence relationships and differing effects among independent and dependent variables. (Hair et al., 2010.)

Second, the relationships proposed are translated into a series of structural equations by the dependent variables of the system specified. SEM also allows model builders to incorporate latent variable constructs into the analysis. Then an unobserved or hypothesised construct is represented by observed or measurable variables. A latent construct variable is measured indirectly through the examination of consistency among indicator variables, also called “manifest variables”, that are collected through different types of data collection techniques such as surveys, tests and observational methods. Measurement model, on the contrary, is used to specify the correspondences between measured variables and latent variable constructs, and it allows any number of indicator variables to be used by single independent or dependent constructs. (Hair et al., 2010.)

Moreover, a latent exogenous construct is a multi-item equivalent of an independent variable that uses a selected variate of measures to represent the construct. Since latent exogenous constructs are acting as independent variables of the model and are determined by the factors outside the model, they are not explained by any other constructs of the model. A latent endogenous construct is a multi-item equivalent to a dependent variable, and it is theoretically determined by the factors within the model and is thus dependent on other constructs. In path diagrams these dependences are visually represented by path arrows which end to endogenous constructs. (Hair et al., 2010; see also Cooper & Schindler, 2008.)

In Figure 5, a thematic structural model is used to represent the interrelationships between the latent variable constructs for IC and KM and the performance construct “OP”. The measurement model, on the contrary, specifies the indicators, i.e. multiple measured variables available in the modelling data, with respect to the constructs of the structural model. A thematic modelling setup in Figure 5 can also be used in interpreting and visualising the mediation effect, i.e. the effect of construct IC on the relationship between KM and OP in which IC is mediating the indirect effect between the other two constructs. The application of mediation is theoretically justified when it is needed to prove, for instance, that not only the direct (see path connections “KM → OP” and “IC → OP” in Figure 5) but also causal chain relationship (KM → IC → OP) between constructs of the model are simultaneously exiting.

SEM is often related to the methods and model estimators that focus on the analysis of covariance structures in relation to the maximum likelihood estimation (Mention & Bontis, 2013). Then reference is commonly made to linear structural relations (LISREL) modelling, a technique based on the covariance structural modelling (Cooper & Schindler, 2008). An increasingly generalising alternative to LISREL and its covariance structural modelling is a Partial Least Squares (PLS) approach based on the analysis of variance that was originally developed for econometrics and was later on adopted in the fields of business and education research and the social sciences (see Hair et al., 2010; also Mention & Bontis, 2013; Sanchez, 2013).

In relation to management research, the studies by Barclay (1991), Helm (2005), Cabrita and Bontis (2008), and Mention and Bontis (2013), for instance, serve as examples of the PLS-based regression applications to structural path modelling-based analyses. According to Sanchez (2013), the PLS approaches for structural path modelling can also be explored form a broader conceptual perspective when there is a need to analyse multiple relationships between blocks of variables that are established based on theoretical phenomenon of interest. Then the path modelling view is emphasised and it is assumed that the blocks established have certain roles to play in the theoretical conceptualisation defined with the aid of latent (unobserved) variables (Sanchez, 2013). Sanchez's (2013) view is corresponding to that of Mention and Bontis (2013) who state that PLS-based path modelling (PLS-PM) can essentially be regarded as an iterative combination of principal component analysis in which measures are related to constructs and path analysis for building a causal chain among the constructs specified.

Even if the structural models of the approaches discussed above look identical, there are true differences between the two procedures including the estimating fundaments already mentioned. In PLS-PM, the structural model and measurement model are often termed inner-model and outer-model, respectively (see e.g., Hair et al., 2010; Sanchez, 2013). The technique *i*) can also handle all types of data, i.e. metric or non-metric, *ii*) is less critical to the assumptions made about the characteristics used in modelling, and *iii*) allows recursive models being identified even with single item constructs (Hair et al., 2010). In PLS, the path coefficient parameters are estimated using regression-based methods (similar to ordinary least squares (OLS) multiple regression), a clear distinction to the maximum likelihood-based approaches (Hair et al., 2010; Monecke & Leisch, 2012; Mention and Bontis, 2013; Sanchez, 2013). In addition, the objective of PLS-PM -based estimation is to maximise the amount of variance explained in the dependent variables of the path model by assuming that all the measured variance is useful variance to be explained, whereas the objective of SEM is to reproduce the observed covariation among the observed measures identified by items (see e.g., Chin, 1997; Hair et al., 2010; Mention & Bontis, 2013).

Mention and Bontis (2013) also discuss about the applicability of PLS-PM and state that the technique is generally recommended for predictive research conducted during the early stages of theory development. The three other advantages of PLS-based path modelling listed by them are as follows: 1) it is suitable for studies conducted using small samples, 2) it does not require assumptions that data are normally distributed, interdependence of observations exists, and uniformity of variable metrics holds (see also, Sosik et al., 2009), and 3) it enables to model the indicator variables either reflectively or formatively (see also, Fornell and Bookstein, 1982). Thus the statements above on the estimators for PLS-based path modelling by Mention and Bontis (2013; see also Sosik et al., 2009; and Fornell and Bookstein, 1982) are in line to those of Hair et al. (2010), for instance.

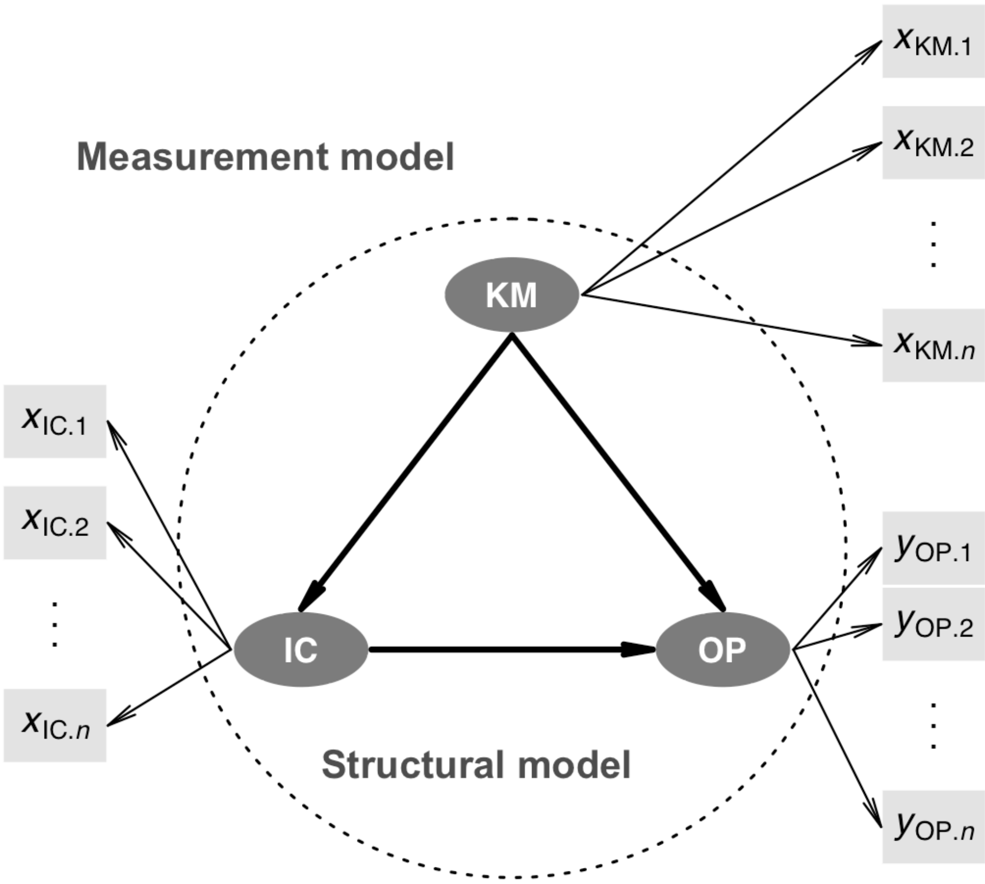

Figure 5. A thematic illustration, i.e. path diagram, for a structural modelling setup of the relationships between latent variables specified by the structural model (i.e., the constructs "IC", "KM" and "OP" within the dashed line circle), and measured or observed items loaded for the independent variables of IC (i.e., $x_{IC.1}$, $x_{IC.2}$,…, $x_{IC.n}$) and KM (i.e., $x_{KM.1}$, $x_{KM.2}$,…, $x_{KM.n}$) and observed outcome variable of OP (i.e., $y_{OP.1}$, $y_{OP.2}$,…, $y_{OP.n}$) specified by the measurement model.

3.3 Selection of estimator and estimation and validation of model parameters

The estimator for the parameters of the structural path models specified in this study was provided by the R package, a free, open-source and cooperatively developed software implemented with the statistical programming language and computing environment of the S software (R core team, 2015). The R package and its ready-to-use functions can also be used in different kinds of procedures related to data processing and statistical testing. It also provides a modeller with efficient functionalities available for making graphical illustrations for variables in data and modelling results, for instance.

Among the many options available in the R programming environment for structural path modelling, a package entitled "semPLS" was first inspected in relation to statistical analyses conducted here (see Monecke & Leisch, 2012). Besides the semPLS, a package provided by the R and shortly entitled "sem" provides the needed capabilities to estimate PLS path models with respect to their parameters (e.g., Fox, 2006). The R package called "plspm" is the third alternative that essentially quantifies the structural relationships specified in the inner-model (i.e., structural model) by considering the network as a system of multiple interconnected linear regressions (Sanchez, 2013).

In this study, the PLS-PM-based estimates for the path coefficients of models 1–6 specified in Figure 3 for testing the validity of hypotheses *H1–H3b* was finally conducted using the R package entitled 'semPLS' developed by Monecke and Leisch (2012). The advantage of semPLS package for PLS-PM by Monecke and Leisch (2012) is that it provides bootstrap-based estimations for outer loadings and path coefficients by leveraging the boot package of R (see also, Canty and Ripley, 2015). The 'semPLS' also calculates confidence intervals by using the percentile method under its summary method (see Monecke & Leisch, 2012). The most important property of the semPLS package that influenced to its selection was related to its stable convergence and capability to produce the bootstrap-based estimates needed for inspecting the significance of path coefficient estimates. It also provides the modeller with a logical programming script which supported the model building in defining the constructs for variables and path dependences needed in describing the relationships between the constructs. The results of model runs can also be visualized with the default plotting functions of the package. This study, however, utilised an additional package “pathdiagram” by Sanchez (2015), an accessory R package for drawing path diagrams in R.

The validation PLS path models was based on the following criteria available in the ‘semPLS’ (Monecke & Leisch, 2012): 1) coefficient of determination (R^2), 2) Stone-Geisser’s Q^2, 3) Dillon-Goldstein’s rho index (*D-G’s* ρ), 4) communality index, and 5) goodness-of-fit (*GoF*) index. R^2 values are used as the coefficients of determination for each endogenous measure in the estimated PLS model. Stone-Geisser’s Q^2 assesses the predictive relevance of the model, whereas the Dillon-Goldstein’s rho is used to measure the “composite reliability” of the model. Communality indices are obtained for the reflectively measure independent variable constructs. Finally, the *GoF* index is used in assessing the general goodness-of-fit of PLS path models. (Monecke & Leisch, 2012.)

According to Aldás-Manzano (2013), for instance, the values of 0.67, 0.33, and 0.19 obtained for R^2 can be regarded as ‘substantial’, ‘moderate’ and ‘weak’ when obtained for endogenous constructs of the model. The model is deemed to have predictive reliability if the value of Stone-Geisser’s Q^2 index is > 0 (Aldás-Manzano, 2013). A critical value for Dillon-Goldstein’s ρ index is 0.7: a block is considered to be homogenous if the value of the index is > 0.7 (Vinzi et al., 2010).

As discussed by Vinzi et al. (2010), the Dillon-Goldstein’s ρ is considered to be a better indicator when compared to Cronbach’s alpha, for instance. The latter of these indices provides a lower bound estimate of reliability and assumes that each manifest variable is assumed to be equally important in defining the latent variable. Dillon-Goldstein’s ρ is only based on the results from the model (i.e. the loadings) rather than the correlations between the manifest variables in the dataset. (Vinzi et al., 2010.)

Communality indices obtained by the reflectively measured independent variable constructs are the averages of the squared correlations between each manifest variable in the given block and the corresponding latent variable scores (Vinzi et al., 2010). *GoF* index, on the contrary, is calculated as the geometric mean of the average values obtained for communality indices and R^2 values of the path model, respectively (Monecke & Leisch, 2012; Vinzi et al., 2010). Due to its dependence on the average communality, the *GoF* is appropriate when assessing path models with reflective measurement models (Vinzi et al., 2010). Because of the fact that there is no overall fit index available in PLS-PM, a global criterion of goodness of fit proposed by Vinzi et al. (2010) is the *GoF* index.

Statistical significance of path coefficients was based on the *t*-test statistics (Aldás-Manzano, 2013; Mention & Bontis, 2013) and 95% confidence intervals (e.g., Vinzi et al., 2010), both of which were obtained for all path coefficient estimates, respectively, by using the bootstrap-derived estimates (Monecke & Leisch, 2012). Path coefficient estimate-wise *t*-statistics were calculated by dividing the coefficient estimates by their bootstrap-based standard error estimates, respectively (e.g. Aldás-Manzano, 2013). This study used 1000 bootstrap samples, a size of sample recommended by Vinzi et al. (2010), even though the 500-sample bootstraps are also commonly applied in testing the significance of path coefficient estimates obtained using PLS-PM (e.g., Monecke & Leisch, 2012; Mention & Bontis, 2013).

4 RESULTS

All the data processing measures were conducted with scripts programmed using the open-source R software (R core team, 2015). The structural path modelling, which was utilised in testing the financial performance of Finnish companies in relation to their KM practices and IC assets, was also conducted with the R and its 'semPLS' package by Monecke and Leisch (2012). The 'semPLS' produced estimates for the path coefficients of the alternative models 1–6 (see Figure 3) and provided with the statistics needed for their validation and for evaluating the significance of parameters obtained based on the bootstrap derived error estimates and confidence intervals. The parameters were estimated in either data with the ROA (n = 227) or ROE (n = 214) used as an objective financial measure of OP and impacted by KM or IC or their different structural combinations specified by models 1–6 (see Figure 3).

In this study all indicators, i.e. measured items, by different asset categories of IC, for instance, were loaded for one single construct "IC" that is illustrated just with the 9 arrows between IC and $INTREL_1$, $INTREL_2$,…, $EXTREL_3$,…, $ENTCAP_6$, respectively, in Figure 6 for model 5 in the dataset for ROA-based performance assessment. As an example and in addition to Figure 6, the printouts of loadings with the names characterising the constructs and items of model 5 in the case of the dependent performance constructs for ROA and ROE are given in Appendices 2a and 2b, respectively. It is worth noting that in the default for the print method of plsSEM, the numeric values of loading objects are printed only for the row maxima and loadings relatively close to them. Thus the loadings shown in the default printing could be used to for checking the discriminant validity of the model analysed with respect to its constructs.

When the values of items directly loaded by model constructs were only inspected, it was observed that a great majority of them attained a value greater than 0.5. In the datasets used to estimate the parameters of model 5, for instance, about 80% of the item-specific loadings took a value greater than 0.5 being 78.9% when ROA was used to specify OP, and 81.7% when ROE was used as a measure for OP (Appendices 2a and 2b). In addition, the values of loadings less than 0.4 obtained for the measured items were very rare. Therefore these data were deemed suitable for PLS-PM.

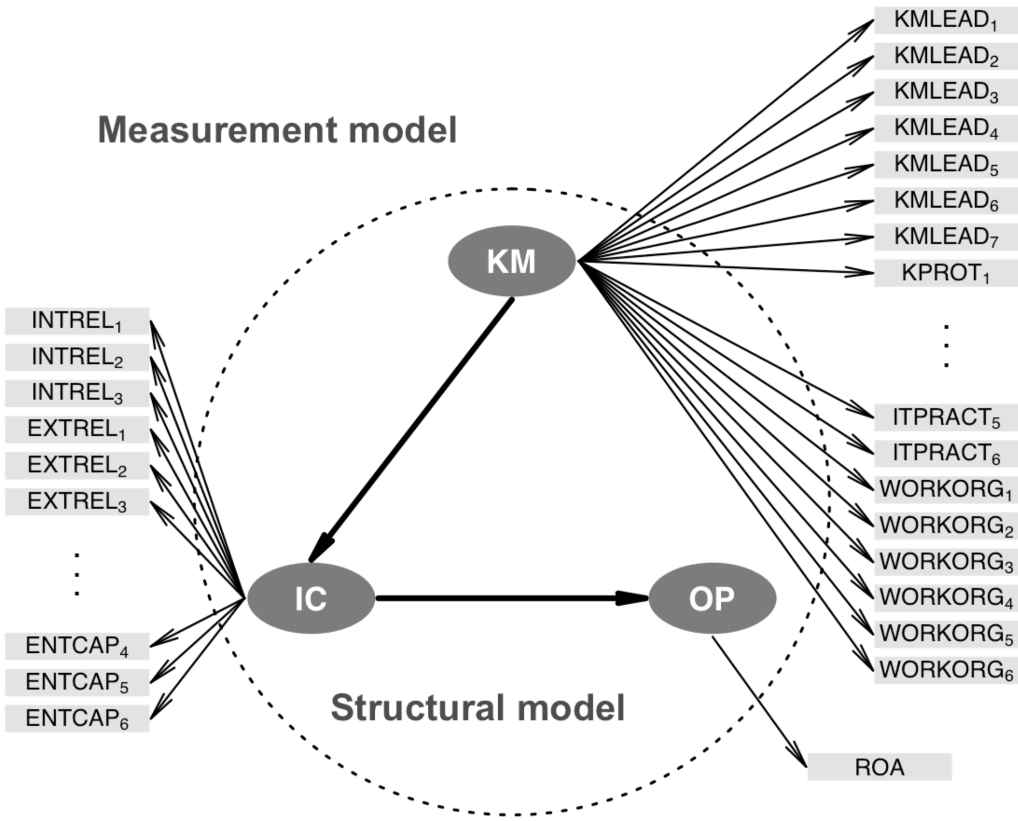

Figure 6. Structural and measurement model specifications for model 5 used in modelling the relationships between the structural model constructs of KM, IC and OP when ROA (*n* = 227) was the indicator selected for the financial performance of companies. The items measured and loaded for KM (i.e., KMLEAD1, KMLEAD 2,…, WORKORG6), IC (i.e., INTREL1, INTREL2,…, ENTCAP6) and OP (ROA) were treated as reflective.

Related to measured indicators, it is also worth noting that all items were treated in PLM-PM in the reflective mode. This was justified because they supposedly mirror the underlying latent variables, i.e. the variable constructs were considered as the cause of the manifest variables, respectively. (See, Sosik et al., 2009; Mention and Bontis, 2013; Sanchez, 2013.)

The structural model would also allow downloading several performance items for the ultimate dependent variable construct, i.e. OP in this case (see Figure 5). In the early stages of the analysis it was thus also tested whether the performance construct of the models 1–6 should combine both of the financial performance indicators, i.e. ROA and ROE. The test statistics obtained for the preliminary models and their parameters showed, however, that no improvement was gained when a construct containing both of the alternative vectors for OP was specified in the structural model. Therefore, the model-based testing of hypotheses was finally based on the two separate sets of data. It was also expected that keeping the two performance indicators separate, i.e. by defining them in an unambiguous manner, the model-based reasoning and assessment of results would be more straightforward to conduct.

Table 4. Statistical validation characteristics obtained for the PLS path models 1–6. R^2 is the coefficient of determination, Q^2 is Stone-Geisser's index for the prediction relevance of the model, *DG's* ρ is Dillon-Goldstein's rho index for the composite reliability of the model, Comm. is communality index, and *GoF* is the goodness-of-fit index of the model.

OP	Variable	model 1	model 2	model 3	model 4	model 5	model 6
ROA	R^2; OP	0.033	0.078	0.079	0.024	0.005	0.019
	R^2; IC	–	–	–	0.676	0.689	–
	R^2; KM	–	–	–	–	–	0.665
	Q^2; OP	-0.018	0.005	0.000	-0.015	-0.004	-0.001
	Q^2; IC	–	–	–	0.220	0.224	–
	Q^2; KM	–	–	–	–	–	0.202
	DG's ρ; IC	0.917	–	0.917	0.937	0.937	0.937
	DG's ρ; KM	–	0.941	0.941	0.952	0.952	0.952
	Comm.; IC	0.292	–	0.292	0.351	0.351	0.351
	Comm.; KM	–	0.277	0.277	0.320	0.320	0.320
	GoF	0.098	0.147	0.150	0.343	0.341	0.339
ROE	R^2; OP	0.035	0.044	0.049	0.013	0.009	0.012
	R^2; IC	–	–	–	0.681	0.689	–
	R^2; KM	–	–	–	–	–	0.681
	Q^2; OP	-0.010	-0.008	-0.009	-0.017	-0.010	-0.010
	Q^2; IC	–	–	–	0.218	0.221	–
	Q^2; KM	–	–	–	–	–	0.196
	DG's ρ; IC	0.925	–	0.925	0.937	0.937	0.937
	DG's ρ; KM	–	0.944	0.944	0.951	0.951	0.951
	Comm.; IC	0.312	–	0.312	0.350	0.350	0.350
	Comm.; KM	–	0.285	0.285	0.316	0.316	0.316
	GoF	0.105	0.113	0.121	0.340	0.341	0.340

The structural path models with estimates obtained for the path coefficients of models 1–6 by the datasets with ROA (n = 227) and ROE (n = 214) are visualised in Figures 7 and 8, respectively. When the validation statistics reported in Table 4 for models 1–6 and their constructs are inspected, it is possible to note that the coefficients of determination obtained for performance constructs ROA and ROE are indicating only weak predictive capability ($R^2 < 0.19$). In the case of endogenous constructs IC (models 4 and 5) and KM (model 6), however, the R^2 values are always varying between 0.67 and 0.69 which indicates a substantial predictive capability of the model with respect to these constructs ($R^2 > 0.67$) and holds true in the case of the both OP constructs.

The values of Stone-Geisser's Q^2 index determined for the endogenous constructs of models 1–6 indicate a poor predictive reliability of the path model when assessed in terms of performance constructs. This is because the index value is practically taken zero or negative when the Q^2 indices for OP are inspected. The index values are always negative when inspected in the case of ROE-based performance modelling results (cf. Table 4). The values of Q^2 index are, however, clearly positive when obtained for IC and KM constructs either in the case of ROA-based or ROE-based PLS-PM.

Block-specific homogeneities of KM and IC constructs are, however, always true when the Dillon-Goldstein's rho (*DG's* ρ) indices are inspected. This is because all the estimates of *DG's* ρs are above the critical value 0.7 as shown in Table 4. Communality indices that are obtainable by the independent variable constructs of the path model are also indicating that the squared correlations by the given blocks are at a moderate level and about the same when the communality estimates for the constructs of models 1–6 are compared between the to modeling setups, i.e. ROA and ROE-based analyses.

Finally, the values *GoF* indices increase systematically when the estimates obtained for models 1 to 3, respectively, are compared that holds true both in the case of ROA-based and ROE-based performance modelling. The estimates of this global criterion of the goodness of fit are however indicating only low fitting success in explaining the variation of the data when obtained for models 1, 2 and 3. The *GoF* estimates in the case of models 4, 5 and 6 are, however, at the moderate level, which is a logical outcome and a result of high R^2 values obtained for the sub-model-constructs for KM and IC (see Table 4).

Therefore, the values of the degree of determination are always larger than 0.3 when the dependency between the items of KM practices and IC assets is modelled, i.e. the path coefficient for KM→IC dependency or IC→KM dependency is included in the structural model.

Table 5. Estimates for the path coefficients of structural path models 1–6 by the modelling data of ROA (n = 227) and ROE (n = 214) with the judgements on the support for hypotheses *H1*, *H2*, *H3a* and *H3b* assessed by inspecting the signs of the path coefficients (Sign) and using the t-statistic-based significance test (Su./t, $p < 0.05$) and 95% bootstrap confidence intervals (*BCI*; Su./b) derived for the lower level (2.5%) and upper level (97.5%) of the interval with the bootstrap of 1000 samples. S.E. is the bootstrap-based estimate for the path coefficient-specific standard error.

OP	Model	Path	Hypothesis	Estimate	S.E.	*t*-test			*BCI*		
						***t*-value**	**Sign**	**Su./*t***	**2.5%**	**97.5%**	**Su./*b***
ROA	1	IC→OP	*H1*	0.182	0.240	0.756	+	No	-0.529	0.261	No
	2	KM→OP	*H2*	0.279	0.200	1.395	+	No	-0.561	0.343	No
	3	IC→OP	*H1*	0.003	0.191	0.013	+	No	-0.461	0.270	No
		KM→OP	*H2*	0.277	0.194	1.428	+	No	-0.537	0.433	No
	4	KM→IC	*H3a*	0.815	0.024	33.675	+	Yes	0.746	0.849	Yes
		KM→OP	*H2*	0.231	0.177	1.310	+	No	-0.149	0.561	No
		IC→OP	*H1*	-0.116	0.184	-0.631	–	No	-0.513	0.223	No
	5	KM→IC	*H3a*	0.822	0.022	36.856	+	Yes	0.760	0.854	Yes
		IC→OP	*H3b*	0.072	0.076	0.951	+	No	-0.116	0.183	No
	6	IC→KM	*H3a*	0.815	0.024	34.568	+	Yes	0.749	0.850	Yes
		KM→OP	*H3b*	0.136	0.067	2.024	+	Yes	-0.064	0.240	No
ROE	1	IC→OP	*H1*	0.188	0.229	0.819	+	No	-0.502	0.283	No
	2	KM→OP	*H2*	0.211	0.254	0.830	+	No	-0.646	0.307	No
	3	IC→OP	*H1*	0.081	0.172	0.471	+	No	-0.420	0.281	No
		KM→OP	*H2*	0.155	0.228	0.681	+	No	-0.566	0.352	No
	4	KM→IC	*H3a*	0.817	0.026	31.731	+	Yes	0.747	0.857	Yes
		KM→OP	*H2*	0.096	0.164	0.587	+	No	-0.314	0.369	No
		IC→OP	*H1*	0.017	0.145	0.120	+	No	-0.289	0.284	No
	5	KM→IC	*H3a*	0.822	0.024	33.685	+	Yes	0.757	0.861	Yes
		IC→OP	*H3b*	0.096	0.097	0.988	+	No	-0.124	0.259	No
	6	IC→KM	*H3a*	0.818	0.025	32.364	+	Yes	0.752	0.858	Yes
		KM→OP	*H3b*	0.110	0.106	1.042	+	No	-0.150	0.285	No

The PLS-PM estimates obtained for the individual, model-specific path coefficients and the assessments on their significance when gathering support for judging the prior hypotheses *H1*, *H2*, *H3a* and *H3b* are summarised in Table 5 (cf. Mention & Bontis, 2013). The estimated coefficients are also visually assessable from Figures 7 and 8 presenting the structural path diagrams of models 1–6 both in the case of ROA-based (Figure 7) and ROE-based (Figure 8) performance modelling of Finnish companies.

When the signs of path coefficient estimates are inspected, it is possible to confirm that hardly any illogicality is related to the path coefficient directions (cf. Mention and Bontis, 2013): the coefficients of all models 1–6 in both of the datasets used in modelling were assumed, a priory, to take positive signs (cf. Table 5; Figures 7 and 8). The only illogical, i.e. negative, sign was obtained for the IC→OP path coefficient of model 4 when ROA was used as a modelled dependent performance characteristic (Table 5, Figure 7). The sign of the corresponding path dependency of model 4 was, however, positive in the case of ROE-based performance analysis (Table 5, Figure 8). In both of the cases, however, the estimates obtained for the path coefficient of model 4 were deemed insignificant based on the *t*-test statistics and analysis of bootstrap-based 95% confidence intervals, respectively, as shown in Table 5.

In the case of the IC assets and their direct effects on OP, the results obtained for model 1 in modelling setups for ROA-based and ROE-based analyses show that there are positive fluctuations between the constructs. The significance tests do not, however, support the hypothesis *H1* in the case of these data derived from the Finnish companies. In the case of model 3, the effects of IC on OP substantially diluted when the path structure KM→OP was simultaneously modelled with the structure IC→OP that was true when assessed using either ROA or ROE as the measure of performance (Table 5). Therefore, it was possible to conclude that the results do not support the hypothesis *H1* unambiguously even when the direct KM→OP effects are completely excluded from the analysis of dependency IC→OP.

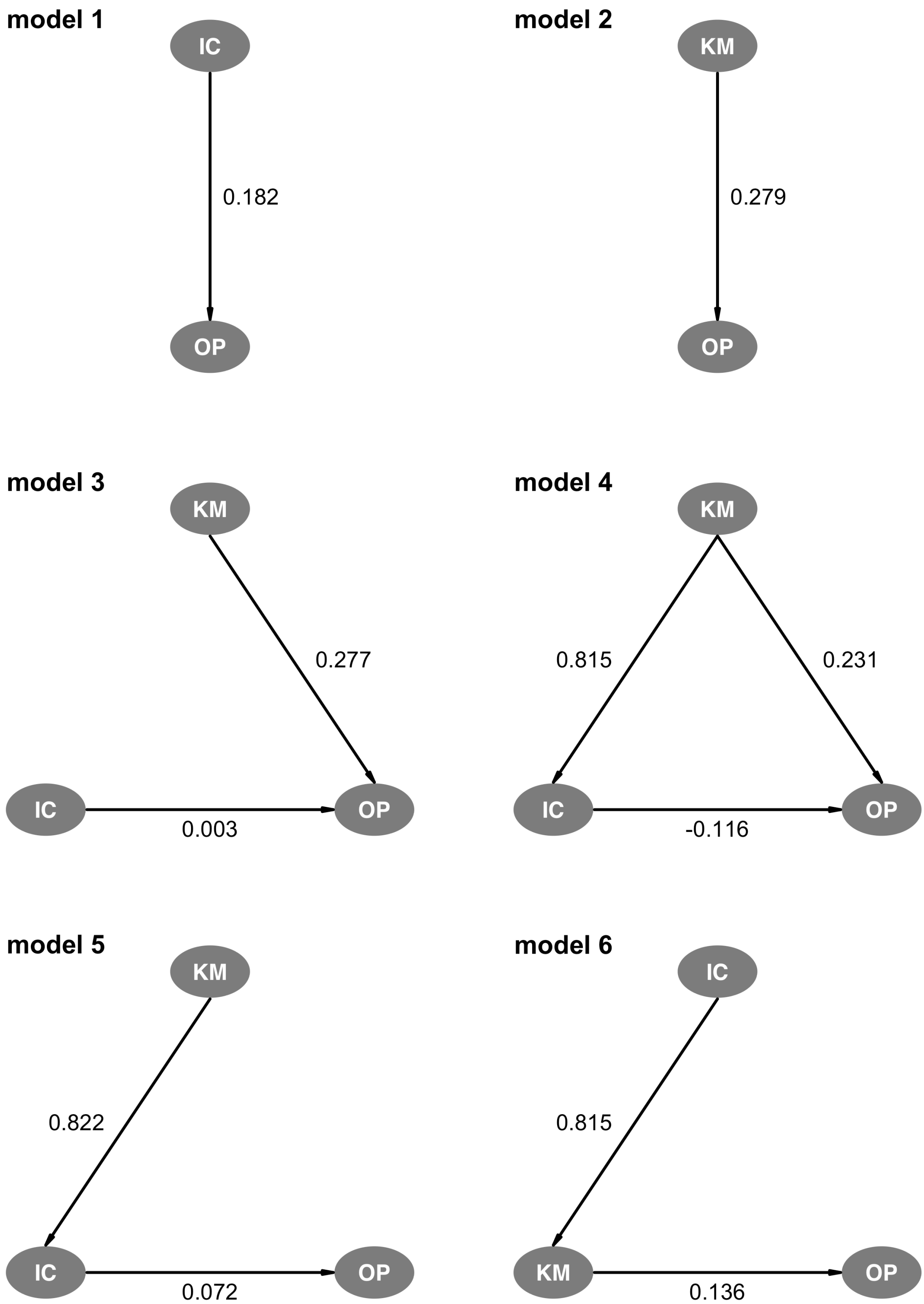

Figure 7. Path diagrams obtained for the six models for testing the hypotheses on the relationships between KM, IC and ROA-based financial OP measure (n = 227).

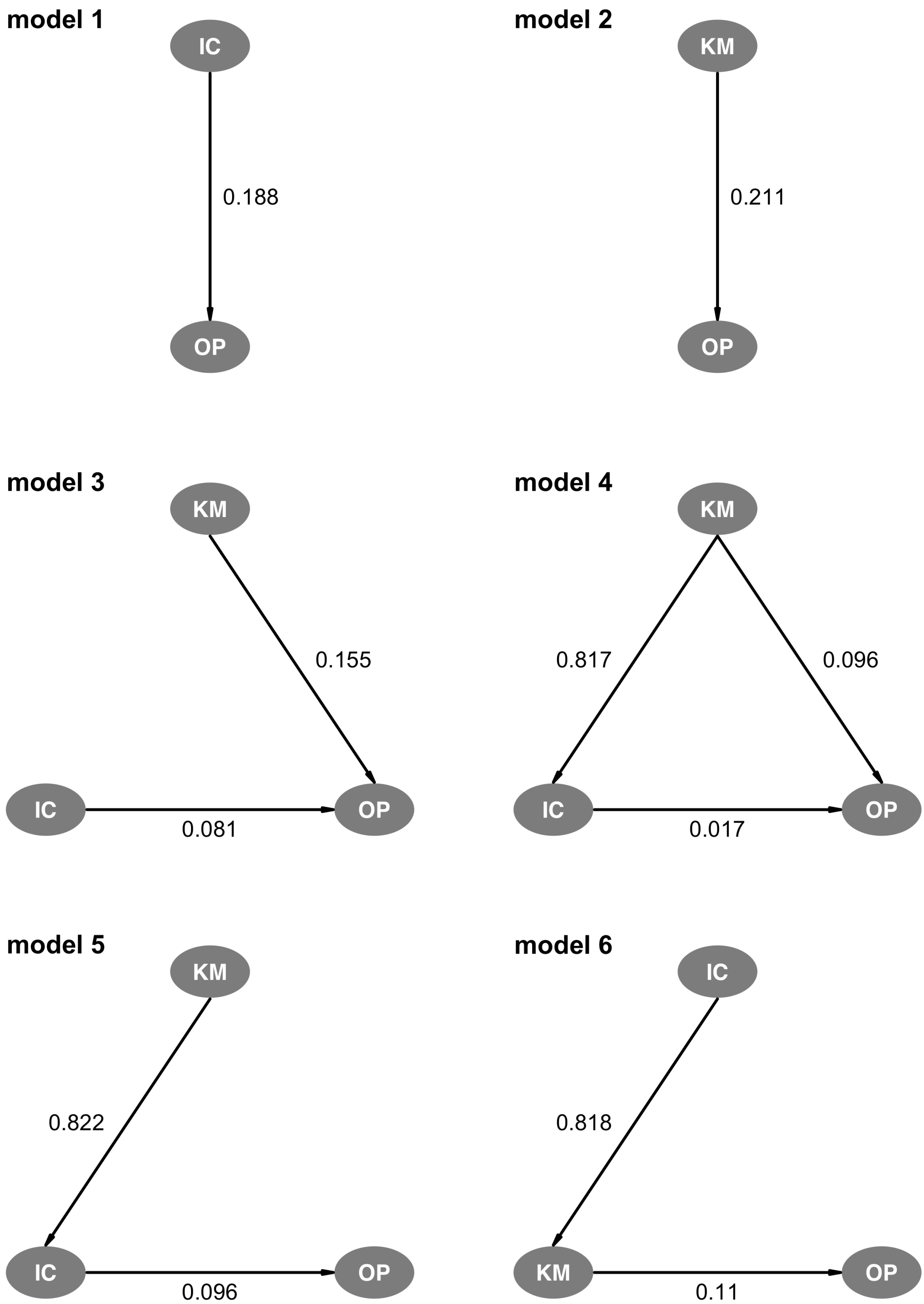

Figure 8. Path diagrams obtained for the six models for testing the hypotheses on the relationships between KM, IC and ROE-based financial OP measure (n = 214).

The results showed that the KM practices operationally utilised in the Finnish companies have positive effects on the financial performance when assessed using either ROA or ROE and when inspected using structural path models 2 and 3, of which the latter model also specified the path dependency IC→OP. Even if the estimated absolute values of these path coefficients between KM and OP are at a relatively high level, the estimates are not significant statistically. Therefore, it was not possible to conclude that the hypothesis *H2* holds unambiguously true in the case of data with ROA, a finding that is also supported by the ROE-based analysis of OP. It is, however, worth noting that the values of estimates obtained for dependence relationships between KM and OP are always higher when compared to those of IC and OP when results for models 1 and 2 are compared, and path coefficient estimates obtained for model 3 are compared, which is true in either ROA-based analysis or ROE-based analysis.

Models 4 to 6 were used to analyse explicitly simultaneous and causal dependences between the modelled constructs. All of the models 4–6 contained a path dependency modelled between KM construct and IC construct. In the “full model” 4, the direct effects between KM and OP were estimated together with the indirect effects between KM and OP mediated by IC, the latter of which was the ultimate target of modelling in the case of the structural construct specification of model 5.

With respect to all models 4–6, the estimate of interaction between the construct for KM practices and the construct for IC assets was strongly significant regardless of the performance characteristic used in modelling: the assumption made on hypothesis *H3a* holds clearly true in the case of these data.

In the case of model 4, the dependencies modelled with ROA-based and ROE-based OPs were insignificant not only in the case of dependency KM→OP but also in the case of IC→OP suggesting that in the completely and explicitly simultaneous modelling situation the strong dependency between KM→IC diluted effects fluctuating between all other dependences. In the case of ROA-based modelling the estimate obtained for the path dependency KM→OP of model 4 attained, however, a relatively high coefficient value 0.231 with *t*-test value of 1.31 (Table 5).

In relation to the overall analysis of results obtained for the simultaneous structural modelling specifications and mediation effects only and using either IC as a mediator (model 5) or KM as a mediating construct (model 6), the dependences IC→OP (model 5) and KM→OP (model 6) were always insignificant, except in the case of model 6 when assessed in the data with ROA-based performance measure and inspected with *t*-test. Even then, however, the bootstrap-based boundary estimates for the 95% confidence interval suggested that the effect between KM and OP was insignificance. It is therefore concluded that the results of this study did not provide completely supportive evidence needed for judging that the hypothesis *H3b* holds true in all circumstances using data available from the Finnish companies. Again, the estimates obtained for IC→OP dependency (model 5) and KM→OP dependency (model 6) indicate – even if they are deemed insignificant – that the KM is impacting OP more than IC is impacting OP, which is also the case when path coefficient estimates of model 4 are inspected.

The results obtained for models 1–6 are quite the same when comparisons of the fit statistics of models and the path coefficient estimates are made between the results obtained for the ROA-based and ROE-based analyses (Tables 4 and 5). When the summary statistics of Tables 1 and 2 and the correlations between the survey-based items and financial performance characteristics classified by the sub-categories of KM and IC and given in Appendices 3a and 3b are inspected, it is possible to conclude that the differences between the two datasets are only minor. Regarding the tabulated Pearson correlations available in Appendices 3a and 3b, the finding is especially clear when the means of correlations by the subcategories of KM and IC are inspected over the complete datasets used to model ROA (Appendix 3a, n = 227) and ROE (Appendix 3b, n = 214) -based performances of Finnish companies. It is thus worth believing that these findings on data explain, at least to some extent, the similarities of results obtained for the models 1–6 when either ROA or ROE was used in constructing the dependent variable for the structural models tested (Tables 4 and 5).

The classified Pearson correlations tabulated by the KM and IC items in the subcategories of the ROA-based data (Appendix 3a) and the ROE-based data (Appendix 3b) provide, however, some indication about the possible differences between companies when inspected in separate subsets of data and classified according to their number of employees

($N_{employees}$) as follows: 1) $N_{employees} < 200$, and 2) $N_{employees} \geq 200$. Even if the means of correlations by the KM-item and IC-item classes remain low, the correlations are systematically higher and attain positive signs when determined for the companies with the number of employees equal to or greater that 200. This finding holds true both in the case of the ROA-based performance indicator (Appendix 3a) and in the case of the ROE-based indicator (Appendix 3b).

In the case of a robust industry-based classification “construction and manufacturing companies”, which was obtained for TOL2008 classes 6 and 7, versus “non-construction and manufacturing companies”, which was obtained for TOL2008 classes 1, 2, 3, 4, 5 and 8, the differences were rather minuscule when the means of classified item-specific correlations obtained with respect to the ROA-based performance indicator and the ROE-based indicator were compared (cf. Appendices 3a and 3 b). In the case of the means of the classified correlations obtained between the items of KM and ROE and IC and ROE, the means of correlations were, however, higher when tabulated for the companies belonging to TOL2008-calsses 1, 2, 3, 4, 5, and 8 (n = 112) when compared to those of the TOL2008-classes 6 and 7 (n = 102). In addition, the means of correlations by the subcategories of KM and IC were always positive when obtained for the group of companies representing the “non-construction and manufacturing companies” (n = 112) in data for the analysis of OP based on ROE.

5 DISCUSSION

5.1 Theoretical implications

The main objective of this study was to test whether the hypothesised positive direct impacts of IC assets (*H1*) or KM practices (*H2*) or their simultaneous relationships (*H3a* and *H3b*) on the financially measured OP hold true in the case of data collected from the sample of Finnish companies of varying size and representing different fields of industries In this study, OP was defined using either ROA or ROE for measuring the performance of companies. The model-based testing approach of the study hypotheses utilised a structural modelling concept with six alternative models for different combinations of KM, IC and OP (see Figures 3, 7 and 8). Path coefficients of all models were estimated using a PLS-PM technique (e.g., Monecke & Leisch, 2012; Mention & Bontis, 2013; Sanchez, 2013).

Among the six structural path models tested, models 1 and 2 were used in modelling the direct effects between IC and OP only or KM and OP only, respectively. The remaining four structural path models were received for analysing simultaneous effects between the modelled interactions of the constructs for IC, KM and OP. One of the models for simultaneous effects tested direct effects between KM and OP and IC and OP without the path specification for the KM→IC dependency, whereas three other models contained also structural specifications for testing the mediation effects for the causal chain dependencies KM→IC→OP (IC mediates) and IC→ KM→OP (KM mediates) (cf. Kianto et al., 2014).

When the interaction between IC and OP was analysed without even seemingly unrelated effects caused by the interaction between KM and OP, the estimate obtained for the path coefficient of the IC→OP dependency appeared to be insignificant based on the bootstrap derived *t*-test statistic and confidence interval when using either ROA or ROE as a measure for performance. This dependency was also insignificant when only the KM→OP dependency was simultaneously modelled using either ROA or ROE to specify the dependent construct of the structural path model. The direct effect between KM and OP was also always insignificant when analysed either individually or with path dependency for IC→OP specified in the structural model.

The relationship between IC and KM was very strong and significant in all possible simultaneously modelled combinations of dependences between the construct specifications tested using models 4–6. In the case of models 4-6, KM and IC were also treated as mediators of effects between the three constructs modelled. In these cases, the dependences tested were as follows: 1) causal chain "KM→IC→OP" with the dependency "KM→OP", i.e. the full model, 2) causal chain "KM→IC→OP" only, and 3) causal chain "IC→KM→OP" only. When the significances of the path coefficients were inspected based on the bootstrap confidence intervals, all estimates obtained for the dependencies "IC→OP" (model 5) and "KM→OP" (model 6) and using either ROA or ROE as the indicator of OP were deemed insignificant. An interesting result was obtained, however, when these assessments on the path coefficient estimates were conducted based on *t*-test statistics: the dependency between KM and OP constructs was significant when ROA was used as a performance measure in modelling the causal chain "IC→KM→OP" with model 6. In that case, the lower boundary (2.5%) of the bootstrap 95% confidence interval was also close to zero, i.e. the estimate for the path coefficient was close to significant (see Table 5).

Generally, it is possible to conclude that the absolute values of estimates obtained for path coefficients of dependencies IC→OP and KM→OP varied moderately and attained even as high values as ca. 0.28 that was the case with KM→OP dependency using model 2 in ROA-based analysis of OP. The estimates obtained for the dependencies KM→OP and IC→OP indicated a stronger relationship between the explanatory construct KM and the dependent construct OP when compared to the relationship between the constructs of IC and OP. The relatively high absolute values of path coefficients seemed to suggest that KM, especially, was impacting OP. These results obtained and inspections conducted using bootstrap-derived confidence intervals and standard errors of path coefficient estimates also used in *t*-tests revealed, however, that the path coefficient estimates obtained for the dependencies KM→OP and IC→OP were affected by clear uncertainties. Therefore, the estimates of path coefficients of dependencies "IC→OP" and "KM→OP" were unambiguously insignificant in all cases except one with model 6 when modelling OP using ROA-based performance measure in inspecting the causal chain "IC→KM→OP".

It is also worth noting that in one case only, i.e. when OP was modelled using ROA with model 4, the sign of the modelled dependency was unexpectedly against expectations, i.e. a negative value was obtained for the IC→OP dependency. Even then, however, the estimate obtained was clearly insignificant. Therefore, it is possible to conclude that the modelling results did not reveal conspicuous inconsistences when inspecting the signs of the path coefficients (cf. Mention & Bontis, 2013).

Based on the results obtained using the PLS-PM suggest that the hypotheses *H1* and *H2* on the direct effects between IC and OP, and KM and OP, respectively, did not hold true. Therefore, the modelling results of this study did not confirm and verify the hypothesis *H1* and are in that respect inconsistent to those earlier reported and discussed, for instance, by Mention and Bontis (2013), Bornemann and Wiedenhofer (2014), Massaro et al. (2015), Nimtrakoon (2015) and Inkinen (2015). The results reported here in relation to the hypothesis *H2* are parallel to those obtained for assessing *H1*, i.e. the earlier findings on the positive impacts of KM practices on OP reported by Gold et al. (2001), Lee and Choi (2003), Chourides et al. (2003), Chuang (2004), Darroch (2005), Andreeva & Kianto (2012), Lee et al. (2012), Massingham & Massingham (2014), for instance, were not statistically proven in the data of this study.

Based on the findings discussed above it is worth repeating the first research question (RQ1) of this study that asked: “Are the theoretically assumed causal effects of IC assets and KM practices positively impacting OP also empirically proven?” After this preliminary modelling study conducted, it is difficult to give any unambiguous answer to the research question above, i.e. a less definitive answers and explanations to the partly unexpected results are only provided at this stage of analysis. They are elaborated in the following.

The hypothesis *H3a* on the positive effects between KM and IC was proven unambiguously true, and the interaction was strongly significant even when other specifiable path dependencies were simultaneously modelled. This study was, however, capable to find only some indicative evidence for the verification of the hypothesis *H3b* suggesting that KM practices and IC assets are causally related with positive impacts on OP, i.e. either KM or IC acts as the mediator. This means that the earlier mediation assumptions derived from the KBV by Grant (1996), i.e. emphasising the static and dynamic aspects of organisational knowledge-based value creation, cannot be directly and unambiguously acknowledged based on the results obtained using these model specifications and data available from the Finnish companies (Kianto et al., 2014). The causal dependency "IC→KM→OP", which was significant when ROA was used as an indicator of OP and tested based on *t*-statistic, is however an interesting finding and may provide valuable indication needed in disclosing the true relationships and causal dependences between the three modelled structural constructs.

Even if the results of this study did not provide unambiguous support for the hypotheses set on the mediation effects for the dependences "KM→IC→OP" or "IC→KM→ OP", which were initially proposed by Kianto et al. (2014), it does not, however, mean that the assumptions on the fluctuations of effects between them does not hold true. The observations gave some indication about the indirect effects of IC on OP mediated by KM. Therefore, it is worth assuming that the influence mechanisms associated to the phenomenon are more complex and cannot be directly and completely detected by using the general model constructs structured in this study: its theoretically sound foundation should not be deemed unjustified because of the findings presented here. The results of this study should thus be regarded as preliminary. This judgement is necessary, especially, because the direct effects between IC and OP, and KM and OP in testing hypotheses *H1* and *H2*, respectively, i.e. when the impacts by the dependencies between KM and IC were not specified in the structural model, appeared to be insignificant. The apparent uncertainty related to the estimates obtained for the path coefficients of IC→OP and KM→OP dependencies in these data requires further investigations.

Since the KM practices were impacting positively but insignificantly OP as were the IC assets impacting OP, it is possible to propose a question for continuing the discussion: "Why the strong and positive interaction observed and verified between KM and IC was not unambiguously significantly influencing OP in the case of Finnish companies subject to this study?" A straightforward argument based on these findings could, for instance, simply suggest and explain that KM practices are affecting positively IC but that this dependency does not result to the improved financial performance of the companies in these data.

There are, however, several possible and alternative explanations for the insignificant path coefficient estimates obtained in this study. First, it is possible that the effects of items measured by KM and IC are diluted when downloaded just by individual, i.e. single, “upper-level” constructs specified with respect to KM and IC. Second, it is also possible that some combinations of items are incorporating not only ineffective but also negative impacts to the pooling construct that may neutralise their combined effects. Third, it is still possible that some of the items measured by KM and IC indicate the same effects while reflecting to OP, i.e. they are overlapping. This can lead to a situation where the model should, in fact, be deemed overparameterised even if the items are seemingly unrelated when categorised by the two components used to predict the third (cf. Kianto et al. 2014). The results obtained for model 4, for instance, can be assessed in light of the third explanation proposed above.

Re-assessing and examining whether or not the items measured are overlapping is also important from the theoretical perspectives: the items measuring IC should indicate the efficiency and effectiveness of managerial governance of intangibles, i.e. factors influencing and operating at the strategic level, whereas the items measuring KM should be defined and targeted to indicate the operational and tactical, knowledge related processes and practices only (cf. e.g., Wiig, 1997; Kujansivu, 2008). These possible contradictions between the effects of downloaded items of structural model (i.e. inner-model) constructs should be inspected and excluded for making the analysis between the true causal effects of IC and KM impacting OP more legitimate and unambiguous. It is also possible that by using a reduced number of items in modelling the IC and OP dependency and KM and OP dependency will produce significant estimates for these between-effects of constructs specified by models 1 and 2, respectively, or even when analysed simultaneously with model 3.

5.2 Findings on path modelling and data-related issues

The analysis was conducted by using either ROA or ROE as the measure of OP, a modelling setup that was selected for assessing differences between the validation statistics obtained for models and significance measures determined for path coefficient estimates with respect to the two performance measures. It was also of interest to gain new information about the two financial performance measures and their behaviour in relation to the KM- and IC-based characteristics. Due to the negative values of equity reported in the financial statements, the values of ROE were incalculable in the case of some companies. In spite of the slight difference between the resulting datasets with either ROA (n = 227) or ROE (n = 214) used as a performance measure, an overall observation was that the modelling results obtained with respect to the two datasets were almost parallel.

When the IC assets itemised and measured by the Finnish companies were analysed using the path models without the dependence KM→IC, the results were somewhat different when compared to those obtained by specifying the effects by KM practices in the structural model. When the effects for the dependence KM→OP were estimated together, i.e. simultaneously, with IC→OP, two conclusions were derivable: 1) KM had dilutive impacts on the estimates obtained for the dependency between IC and OP, and 2) the simultaneous effects by IC affected the dependency estimated for the relationship between KM and OP in the dataset for ROE-based assessment of OP.

In the case of the "full model" 4, not only the dependency KM→OP but also the causal dependency KM→IC→OP was specified in the structural model, which in ROA data led to the only illogical, i.e. negative, sign obtained among any of the path coefficients estimated for models 1–6 in either of the datasets. Even if the estimate with a negative sign was deemed insignificant, its appearance in this context was interesting. One explanation for this outcome could be that in the simultaneous estimation of direct effects of KM and IC on OP, which are clearly dominated by KM also based on the results obtained for models 1 and 2 in ROA data, the dependency KM→OP is also diluting the indirect effects simultaneously fluctuating through the modelled causal dependency KM→IC→OP and suppressing, finally, the effects between IC and OP. Interestingly, the path coefficient for the same relationship in model 4 was positive when ROE, instead, was used to indicate the performance of companies.

This difference is revealing and may indicate inconsistences within the data with ROA (n = 227) that contains also items for KM, IC and OP also obtained for those companies for which ROE (n = 214) was not obtainable due to the negative value of equity extracted from the financial statements of 2014. The estimate obtained for the path coefficient in question was deemed insignificant also in the case of ROE data, however.

When the properties of the study data in relation to results obtained are analysed, it is possible to conclude that eliminating the data rows with the sub-categories of KM and IC that contained missing values of items was justified. It is also expected that this had positive impacts on structural modelling conducted. It was in this respect that Sanchez (2013), for instance, recommended that assessments on data containing missing values and treating them, if needed, be conducted for improving the properties of data used in PLS-PM and model-based testing of hypotheses. It is worth mentioning, however, that ‘plspm’ did not converge when the bootstrap estimates of standard errors and confidence intervals were tried to obtain for the PLS estimates of the path coefficients even if PLS estimates were obtained with a call for the numeric scaling: ‘plspm’ works limitedly with data that contain missing values. Due to the fact that only approximate error estimates and, therefore, t-test statistics for the parameters were obtained with the ‘plspm’, the models were finally estimated using the semPLS package that was capable to converge and produce the bootstrap estimates needed for testing the significance of the path coefficients.

Treating the missing values is crucial, especially, when constructs are obtained with a limited number of items, even though PLS-PM allows to model constructs with only one measured item loaded for them (see also, Hair et al., 2010), which was the case regarding the construct for OP of this study. If all items with respect to a single structural construct contained missing values within one row of data, it would result into the non-convergence of the PLS-PM estimator (Sanchez, 2013). That was also verified in the early stages of this study. Due to the relatively low number of missing values with respect to the data used in this study, the issues related to missing values were tackleable in the PLS-based estimation without applying any data imputation procedures (e.g., Roth et al., 1999). Testing the significance of estimates obtained for the PLS path model coefficients parameters required, however, that a bootstrapping procedure was applied. The bootstrap confidence intervals and standard errors for the estimated path coefficients were obtained using the PLS-PM tool by Monecke & Leisch (2012) without any convergence problems.

The PLS-PM package 'semPLS' by Monecke & Leisch (2012) available in the R (R Core Team, 2015) proved to provide a technique appropriate for testing hypotheses set on the direct and indirect effects of KM practices and IC assets on the financially measured OP using data available from Finnish companies. Thus, the findings obtained and experiences gained in the case of this study verify and support the earlier conclusions by Mention and Bontis (2013) and van Reijsen et al. (2015), for instance. Therefore, it is possible to conclude that PLS-PM approach suitable for examining survey data collected from companies when testing assumptions derived from the KBV (Grant, 1996) in connection to RBV (see Barney, 1991).

The second research question (RQ2) asked: "How appropriate is the structural path modelling-based analysis for assessing the interactions between the constructs of KM, IC and OP using a multisource data with different scales?" Based on the results of this study and discussions above, it is recommended that structural path modelling be used as a technique for analysing the relationships between KM, IC and OP even when their items measured are obtained from different sources of data. It is also possible to conclude that the analysis and visualisation tools available in the R calculation and analysis environment, which were used in addition to the 'semPLS' package, provide modellers with a compact and flexible and, therefore, efficient set of procedures and features needed in tackling the complexities related to empirical IC, KM and OP data and hypothesis testing about their assumed causal interactions.

5.3 Findings on financial measures and practical implications

This study used both ROA and ROE as objective financial measures of company performance. Results show that these two characteristics are valid measures in the PLS-PM-based testing of hypotheses with KM- and IC-related constructs obtained using survey-based items. There are, however, examples of econometrical and managerial studies that used either survey based items (e.g., Mention & Bontis, 2013) or account-based, financial items (e.g., Tanriverdi & Venkatraman, 2005) as measures of performance. Moreover, the issues related to a survey data-originating common method bias, i.e. items by modelled constructs are obtained from the same respondents, were also solvable by utilising these two financial OP measures (cf., Isaac et al., 2010; Kianto et al., 2014). By obtaining the performance measures from the two financial databases instead of using the survey-based OP data, the measurement bias, which can arise from the way the questions are asked, was also avoided in relation to performance indication (see Hair et al., 2010).

It was also a quite interesting finding that the results obtained using the two performance indicators were almost parallel even if the magnitude of variation obtained for ROE was substantially larger when compared to that of ROA (see e.g., Figure 4). It is recommended, however, that in the forthcoming studies both of the variables still be used but be kept as separate for increasing our understanding of the properties, usability and case sensitivity of these two company performance indicators. Assessing their performance in different subcategories of data (e.g., by industry and size categories) and over time (longitudinal analysis) would also be of interest in this respect.

The findings above reveal, however, that using financial, accounting-based characteristics in the measurement of OP may result in problems that are unsolvable without eliminating "exceptional" performance observations together with other items obtained for the given companies. This is the case, especially, when cross-sectional data from one time point are used. In the case of this study, however, the financial statements of companies showed that the economical recession, which has continued throughout the past several years, has affected their book values. The values of equity, especially, have also been constantly diminishing in the case of many companies that were analysed in this study.

According to Statistics Finland (2015b), the seasonally adjusted gross-domestic product (GDP) of Finland has almost continuously degreased since 2012 and had a clearly diminishing pattern since that turning year. In addition, the growth rate of GDP of Finland was below the mean of EU member countries during the second quarter of 2015 (Eurostat, 2015). Moreover, the output of the national economy of Finland was still felling in September 2015 (Statistics Finland, 2015b). Instead of using the absolute value of ROE from one time point, for instance, it could be more justifiable to utilise its rate and direction of development as the performance indicator when developing the structural path model-based testing for OP. Thus an improved dynamicity of the data containing financial measures would be obtained (cf. Tanriverdi & Venkatraman, 2005). By using repeatedly measured data, the differences between companies in terms of OP could be more properly verified through the analysis of the development patterns of the two financial performance characteristics. In addition, accidental degreases or increases of ROA and ROE affecting the modelling results could be minimised or even eliminated.

Even if the results of this study cannot be directly used to provide the managers with operational instructions or guidelines, its findings and metrics can be used to develop the interpretability of results to be obtained in forthcoming performance modelling studies. Then the performance indicators used here will provide the managers operating with IC-related procedure at the strategic-level or with tactical KM practices and processes at the operational-level with metrics which meaning and definition is clear to them. It is also expected that using these metrics would also assist managers of companies to elaborate their monitoring and reporting procedures on IC, for instance (cf. Mention & Bontis, 2013).

The third research question (RQ3) asked: How suitable are the measures obtained from the financial databases to determine OP? The results and findings discussed and elaborated above show that there are both scientific arguments and practical arguments clearly suggesting that the ROA and ROE type of financial measures obtained from the financial databases are recommendable for the performance analyses of companies.

5.4 Limitations and future research

For understanding the simultaneous effects of KM and IC interaction on OP, a more proper analysis of latent constructs would be needed. Even if the analysis of estimated loadings and correlations by the items of KM and IC constructs did not show any clear deviances, it is possible that the constructs of this study are too general for specifying fluctuations of KM and IC effects impacting OP.

There are different possibilities to continue modelling from these preliminary results reported herein. One alternative is to start examining the loadings and excluding the least effective items from the loadings obtained for different constructs. In that respect the listings of loadings by measured items would provide with one starting point for further analyses. The assessment of correlation tables could also provide insights to the selection of more efficient combinations of measured items by the constructs.

It would also be possible to develop the structural model by defining higher order constructs for IC and KM. Then the seven sub-categories of the IC and KM, respectively, would be treated as separate latent constructs of the first order to be linked with the second order latent constructs of IC and KM (cf. Jiménez-Jiménez & Sanz-Valle, 2011). In this alternative, the second order latent constructs would, therefore, form higher order variables created for pooling the effects from their logical sub-constructs. The advantage gained from this technique would be that the effects of the IC and KM constructs by theirs sub-categories could be analysed simultaneously. The modelling approach based on the first and second order constructs has a direct resemblance to the study by Jiménez-Jiménez and Sanz-Valle (2011), for instance, who used a SEM-based approach with data collected from Spanish firms to analyse relationships between innovation, organizational learning and OP.

Instead of applying higher order constructs, one possible path for modelling would be to specify the KM- and IC-related constructs by the individual KM practices (7 categories) and IC assets (7 categories) and model their interactions directly (e.g., Isaac et al., 2010; Mention and Bontis, 2013). Then the setup would be a kind of combination of the approaches applied in the IC/OP case by Mention and Bontis (2013), for instance, and in the KM/OP-related situation by Darroch (2005), for instance. The path dependences between the constructs of the structural path model would increase from the setup of this study (cf. Mention & Bontis, 2013). A more detailed description for the relationships between the IC-based and KM-based characteristics and fluctuations of direct and indirect effects impacting OP would then be obtained, however. A drawback of this approach would be that then it would be very difficult to make general judgements on the total indirect effects of KM on OP, i.e. effects mediated by IC, or total indirect effects of IC on OP, i.e. effects mediated by KM, because of the more specified, detailed and complex structural model specification(s).

Due to the high number of items (43 + 28 = 71) and possible construct combinations of them, finding a structural model specification that could reveal the possible mediation effects of interest would require technical operationalization. One approach worth testing the measurement model by its items would be to conduct discrimination analyses or utilise clustering-based procedures also available for PLS-based estimators (see e.g., Newman et al., 2013; Sanchez, 2013).

Finally, the ultimate target of the selection of items would be to detect the combinations of KM- and IC-based items forming the essential factors for the value creation of companies in Finnish conditions (cf., Grant, 1996; Johannessen et al., 2005; Lönnqvist et al., 2009; Isaac et al., 2010; Kianto et al., 2014; Lerro et al., 2014). In the case of models 5 and 6, for instance, the examination of alternative combinations of items by constructs and searching for an optimal combination of them could be based on the maximisation of the value of the path coefficient for the dependency IC→OP in the case of model 5 or the path coefficient for dependency KM→OP in the case of model 6. Operationalising the item selection could be conducted by applying optimisation techniques (see e.g., Leardi & González, 1998). This would simultaneously reveal new information essential for determining the key factors behind the KM- and IC- related processes and mechanisms which provide the companies with resources and competence needed for obtaining sustainable competitive advantage (e.g., Barney, 1991: Grant, 1996; Spender et al., 2013).

6 CONCLUSIONS

The PLS-PM technique applied was capable to process a 5-point Likert-type scale survey data with altogether 28 items of IC and 43 items of KM together with the financial performance items, i.e. ROA or ROE, extracted from the financial databases by over 200 Finnish companies subject to the analysis of this study. Thus the objectivity of the performance measures used in relation to the survey-based measures itemised by the KM practices and IC assets in testing the study hypotheses was achieved. Thereby the common method bias was also tackled in relation to OP construct and its predictor constructs. The objectivity of data vectors obtained for the items of ROA and ROE used in characterising OP of the Finnish companies makes a clear distinction to many earlier structural modelling studies on the analysis of dependencies between KM practices and OP or IC assets and OP. The interactions between either KM and OP or IC and OP were always insignificant when analysed separate to any other interactions or indirect effects caused by simultaneous modelling, which was true whether ROA or ROE was used as a performance measure in the analysis. The strong dependency between KM and IC hold true in all simultaneous structural model specifications and in the case of both OP characteristics used in testing. In the case of this modelling study, the assumptions on mediation effects did not also hold true except in the case of ROA-based performance testing when KM was specified as a mediator of the effects between IC and OP and *t*-test was used for assessing the significance of the path coefficient estimate. Due to these quite unforeseen results obtained, it is recommended that a more comprehensive analysis of alternative combinations of measured items by the sub-constructs of IC and KM, for instance, be conducted for examining causalities between IC, KM and OP. This needs to be essentially emphasised, because it is possible that the structural model of this study was a too general specification for proving the pre-assumed causality between the three constructs. Therefore, not only the specification of the structural model but also assessments on the modelled characteristics and their development to tackle the possible issues related to the cross-sectional nature of data leave room for the further studies. It is thus also recommended that the current data of 2014 on ROA and ROE be supplemented with new performance data to be gathered from the financial statements of the companies analysed in this study and covering at least this accounting year about to finish.

REFERENCES

Aldás-Manzano, J. (2013). Partial least squares path modelling in marketing and management research: An annotated application. Chapter 3. In: Moutinho, L. & Huarng, K.-H. (Eds), Quantitative Modelling in Marketing and Management. Works Scientific Publishing Co. Pte. Ltd., Singapore.

Alvesson, M. (2004). Knowledge Work and Knowledge- Intensive Firms. Oxford University Press Inc., Biddles Ltd., King’s Lynn, Norfolk, Great Britain.

Andreeva, T. & Kianto, A. (2012). Does knowledge management really matter? Linking knowledge management practices, competitiveness and economic performance. Journal of Knowledge Management, Vol. 16, Iss. 4, pp. 617–636.

Barclay, D.W. (1991). Interdepartmental conflict in organizational buying: The impact of the organizational context. Journal of Marketing Research, Vol. 28, Iss. 2, pp. 145–159.

Barney, J. (1991). Firm resources and sustained competitive advantage. Journal of Management, Vol. 17, No. 1, pp. 99–120.

Berry, H. (2015). Knowledge inheritance in global industries: The impact of parent firm knowledge on the performance of foreign subsidiaries. Academy of Management Journal, Vol. 58, No. 5, pp. 1438–1458.

Bontis, N. (2001). Assessing knowledge assets: a review of the models used to measure intellectual capital. International Journal of Management Reviews Volume 3 Issue 1 pp. 41–60.

Bontis, N. (2004). National Intellectual Capital Index. Journal of Intellectual Capital, Vol. 5, Iss. 1, pp. 13–39.

Bornemann, M. & Wiedenhofer, R. (2014). Intellectual capital in education: a value chain perspective. Journal of Intellectual Capital, Vol. 15, Iss. 3, pp. 451–470 .

Bureau van Dijk. (2015). *amadeus* – A database of comparable financial information for public and private companies across Europe. Amadeus brochure. URL (last visited November 29, 2015): http://www.bvdinfo.com.ezproxy.uef.fi:2048/en-gb/about-bvd/brochure-library/brochures/amadeus

Cabrita, M.R. & Bontis, N. (2008). Intellectual capital and business performance in the Portuguese banking industry. International Journal of Technology Management, Vol. 43, Nos. 1–3, pp. 212–237.

Canty, A. & Ripley, B. (2015). boot: Bootstrap R (S-Plus) Functions. R package version 1.3-17. URL (last visited November 29, 2015): https://cran.r-project.org/web/packages/boot/index.html

Castillo, J. (2003). Challenging the knowledge management mystique – An exploratory study on the performance of knowledge managing companies. Journal of Management Research, Vol. 3, No. 3, pp. 152–172.

Chen, M.-C., Cheng, S.-J. & Hwang, Y. (2005). An empirical investigation of the relationship between intellectual capital and firms' market value and financial performance. Journal of Intellectual Capital, Vol. 6, Iss. 2, pp. 159–176.

Chin, WW. (1997) Overview of the PLS Method. URL (last visited November 29, 2015): http://disc-nt.cba.uh.edu/chin/PLSINTRO.HTM

Chourides, P., Longbottom, D. & Murphy, W. (2003). Excellence in knowledge management: an empirical study to identify critical factors and performance measures. Measuring Business Excellence, Vol. 7, Iss. 2, pp. 29–45.

Chuang, S.H. (2004). A resource-based perspective on knowledge management capability and competitive advantage: an empirical investigation. Expert Systems with Applications, Vol. 27, Iss. 3, pp. 459–465.

Clarke, M., Seng, D. & Whiting, R.H. (2011). Intellectual capital and firm performance in Australia. Journal of Intellectual Capital, Vol. 12, Iss. 4, pp. 505–530.

Cooper, D.R. & Schindler, P.S. (2008). Business Research Methods. Tenth Edition. International Edition. McGraw-Hill/Irwin, Singapore.

Darroch, J. (2005). Knowledge management, innovation and firm performance. Journal of Knowledge Management, Vol. 9, Iss. 3, pp. 101–115.

Edvinsson, L. (1997). Developing Intellectual Capital at Skandia. Long Range Planning, Vol. 30, No. 3, pp. 366–373.

Edvinsson, L. (2013). IC 21: reflections from 21 years of IC practice and theory. Journal of Intellectual Capital, Vol. 14, Iss. 1, pp. 163–172.

Eisenhardt, K.M. & Martin, J.A. (2000). Dynamic capabilities: What are they? Strategic Management Journal, Vol. 21, Iss. 10–11, pp. 1105–1121.

Eisenhardt, K.M. & Santos, F.M. (2006). Knowledge-Based View: A New Theory of Strategy? In: Pettigrew, A., Thomas, H. & Whittington, R. (Eds), Handbook of Strategy and Management, SAGE Publications Ltd, London, pp. 139–165.

Erikson, T. (2002). Entrepreneurial capital: the emerging venture's most important asset and competitive advantage. Journal of Business Venturing, Vol. 17, Iss. 3, pp. 275–290.

Eurostat. (2015). Euroindicators. News release 152/2015-8, September 2015. URL (last visited November 29, 2015): http://ec.europa.eu/eurostat/documents/2995521/6980288/2-08092015-AP-EN.pdf/0f304d15-38ab-4ec3-a972-d0aa2ce0baf8

Feng, K., Chen, E.T. & Liou, W. (2004). Implementation of knowledge management systems and firm performance: an empirical investigation. The Journal of Computer Information Systems. Vol. 45, Iss. 2, pp. 92–104.

Finnish Patent and Registration Office. (2015). Virre online information service by The Finnish Patent and Registration Office (PRH). URL (last visited November 29, 2015): https://www.prh.fi/en/kaupparekisteri/tietopalvelut/online_services/virre.html

Firer, S. & Williams, S.M. (2003). Intellectual capital and traditional measures of corporate performance. Journal of Intellectual Capital, Vol. 4, Iss. 3, pp. 348–360.

Fornell, C. & Bookstein, F.L. (1982). Two structural equation models: LISREL and PLS applied to consumer exit-voice theory. Journal of Marketing Research, Vol. 19, Iss. 4, pp. 440–452.

Fox, J. (2006). Structural Equation Modeling With the sem Package in R. Structural Equation Modeling, Vol. 13, Iss. 3, pp. 465–486.

Gold, A.H., Malhotra, A. & Segars, A.H. (2001). Knowledge Management: An Organizational Capabilities Perspective. Journal of Management Information Systems. Vol. 18, No. 1, pp. 185–214.

Grant, R.M. (1996). Toward a knowledge-based theory of the firm. Strategic Management Journal, Vol. 16, Iss. S2, pp. 109–122.

Hair, Jr., J.F., Black, W.C., Babin, B.J. & Anderson, R.E. (2010). Multivariate Data Analysis – A Global Perspective. Seventh Edition. Pearson Education Inc., Upper Saddle River, New Jersey, the United States of America.

Helm, S. (2005). Designing a formative measure for corporate reputation. Corporate Reputation Review, Vol. 8, Iss. 2, pp. 95–109.

Hillman, A.J. & Keim, G.D. (2001). Shareholder Value, Stakeholder Management, and Social Issues: What's the Bottom Line? Strategic Management Journal, Vol. 22, No. 2, pp. 125–139.

Hussi, T. (2004). Reconfiguring knowledge management – combining intellectual capital, intangible assets and knowledge creation. Journal of Knowledge Management, Vol. 8, Iss. 2, pp. 36–52.

Inkinen, H. (2015). Review of empirical research on intellectual capital and firm performance. Journal of Intellectual Capital, Vol. 16, Iss. 3, pp. 518–565.

Intellia Oy. (2015). An official website of Intella Oy. URL (last visited November 29, 2015): https://intellia.fi/

Isaac, R.G., Herremans, I.M. & Kline, T.J. (2010). Intellectual capital management enablers: A structural equation modeling analysis. Journal of Business Ethics 93, Iss. 3, pp. 373–391.

Jiménez-Jiménez, D. & Sanz-Valle, R. (2011). Innovation, organizational learning, and performance. Journal of Business Research, Vol. 64, Iss. 4, pp. 408–417.

Johannessen, J-A., Olsen, B. & Olaisen, J. (2005). Intellectual capital as a holistic management philosophy: a theoretical perspective. International Journal of Information Management, Vol. 25, Iss. 2, pp. 151–171.

Kianto, A., Hurmelinna-Laukkanen, P. & Ritala, P. (2010). Intellectual capital in service- and product-oriented companies. Journal of Intellectual Capital, Vol. 11, Iss. 3, pp. 305–325.

Kianto, A., Ritala, P., Spender, J.-C. & Vanhala, M. (2014). The interaction of intellectual capital assets and knowledge management practices in organizational value creation. Journal of Intellectual Capital, Vol. 15, Iss. 3, pp. 362–375.

Kujansivu, P. (2008). Operationalising intellectual capital management: choosing a suitable approach. Measuring Business Excellence, Vol. 12, Iss. 2, pp. 25–37.

Leardi, R. & González, A.L. (1998). Genetic algorithms applied to feature selection in PLS regression: how and when to use them. Chemometrics and Intelligent Laboratory Systems, Vol. 41, Iss. 2, pp. 195–207.

Lee, H. & Choi, B. (2003). Knowledge Management Enablers, Processes, and Organizational Performance: An Integrative View and Empirical Examination. Journal of Management Information Systems, Vol. 20, No 1, pp. 179–228.

Lee, S., Kim, B.G. & Kim, H. (2012). An integrated view of knowledge management for performance. Journal of Knowledge Management, Vol. 16, Iss. 2, pp. 183–203.

Lerro, A., Linzalone, R. & Schiuma, G. (2014). Managing intellectual capital dimensions for organizational value creation. Journal of Intellectual Capital, Vol. 15, Iss. 3, pp. 350–361.

Lönnqvist, A., Kianto, A. & Sillanpää, V. (2009). Using intellectual capital management for facilitating organizational change. Journal of Intellectual Capital, Vol. 10, Iss. 4, pp. 559–572.

Maditinos, D., Chatzoudes, D., Tsairidis, C. & Theriou, G. (2011). The impact of intellectual capital on firms' market value and financial performance. Journal of Intellectual Capital, Vol. 12, Iss. 1, pp. 132–151.

Marr, B. (2006). Strategic Performance Management – Leveraging and measuring your intangible value drivers. Elsevier Ltd., Butterworth-Heinemann, Jordan Hill, Oxford, Great Britain.

Marr, B., Gupta, O., Pike, S. & Roos, G. (2003). Intellectual capital and knowledge management effectiveness. Management Decision, Vol. 41, Iss. 8, pp. 771–781.

Marr, B., Schiuma, G. & Neely, A. (2004). Intellectual capital – defining key performance indicators for organizational knowledge assets. Business Process Management Journal, Vol. 10, Iss. 5, pp. 551–569.

Massaro, M., Dumay, J. & Bagnoli, C. (2015). Where there is a will there is a way. Journal of Intellectual Capital, Vol. 16, Iss. 3, pp. 490–517.

Massingham, P.R. & Massingham, R.K. (2014). Does knowledge management produce practical outcomes? Journal of Knowledge Management, Vol. 18, Iss. 2, pp. 221–254.

Mayer, R.C., Davis, J.H. & Schoorman, F.D. (1995). An integrative model of organizational trust. Academy of Management Review, Vol. 20, Iss. 3, pp. 709–734.

MC-info Oy. (2015). An official website of MC-info Oy. URL (last visited November 29, 2015): http://www.mc-info.com/

Mention, A.-L. & Bontis, N. (2013). Intellectual capital and performance within the banking sector of Luxembourg and Belgium. Journal of Intellectual Capital, Vol. 14, Iss. 2, pp. 286–309.

Meritum Project. (2001). MEasuRing Intangibles To Understand and improve innovation Management (MERITUM). Final Report. URL (last visited November 29, 2015): http://www.pnbukh.com/site/files/pdf_filer/FINAL_REPORT_MERITUM.pdf

Molodchik, M.A., Shakina, E.A. & Barajas, A. (2014). Metrics for the elements of intellectual capital in an economy driven by knowledge. Journal of Intellectual Capital, Vol. 15, Iss. 2. pp. 206–226.

Monecke, A. & Leisch, F. (2012). semPLS: Structural equation modeling using partial least squares, Vol. 48, Iss. 3, pp. 1–32.

Newman, M.R., Gamble, G.O., Chin, W.W. & Murray, M.J. (2013). An Investigation of the Impact Publicly Available Accounting Data, Other Publicly Available Information and Management Guidance on Analysts' Forecasts. In: Abdi, H., Chin, W.W., Vinzi, V.E., Russolillo, G. & Trinchera, L. (Eds.), New Perspectives in Partial Least Squares and Related Methods. Springer Science+Business Media, New York. pp. 315–339.

Nimtrakoon, S. (2015). The relationship between intellectual capital, firms' market value and financial performance. Journal of Intellectual Capital, Vol. 16, Iss. 3, pp. 587–618.

Nonaka, I., Toyama, R. & Konno, N. (2000). SECI, *Ba* and Leadership: a Unified Model of Dynamic Knowledge Creation. Long Range Planning, Vol. 33, Iss. 1, pp. 5–34.

Prahalad, C.K. & Hamel, G. (1990). The core competence of the corporation. Harvard Business Review. Vol. 68, Iss. 3, pp. 79–91.

Ray, G., Xue, L. & Barney, J.B. (2013). Impact of information technology capital on firm scope and performance: The role of asset characteristics. Academy of Management Journal, Vol. 56, No. 4, pp. 1125–1147.

R Core Team. (2015). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL (last visited November 29, 2015): http://www.R-project.org/

Roth, P.L., Switzer III, F.S. & Switzer, D.M. (1999). Missing Data in Multiple Item Scales: A Monte Carlo Analysis of Missing Data Techniques. Organizational Research Methods, Vol. 2, No. 3, pp. 211–232.

Sanchez, G. (2013). PLS Path Modeling with R. Trowchez Editions, Berkeley. URL (last visited November 29, 2015): http://gastonsanchez.com/PLS_Path_Modeling_with_R.pdf

Sanchez, G. (2015). Introduction to pathdiagram. URL (last visited November 29, 2015): http://gastonsanchez.com/software/intro-pathdiagram.pdf

Schein, E.H. (2010), Organizational Culture and Leadership. Fourth Edition. Jossey-Bass. A Wiley Imprint Publishers, San Francisco, CA, the United States of America.

Schumpeter, J.A. (1983). The theory of economic development. Translated by Redvers Opie from the German original "*Theorie der wirtschaftlichen Entwicklung*" with a new introduction by John E. Elliott. Transaction Publishers, New Brunswick, New Jersey.

Sosik, J.J., Kahai, S.S. & Piovoso, M.J. (2009). Silver Bullet or Voodoo Statistics? A primer for using the partial least squares data analytic technique in group and organization research. Group & Organization Management, Vol. 34, No. 1, pp. 5–36.

Spender, J.-C., Bednarz-Łuczewska, P., Bordianu, A. & Rohaert, S. (2013). Intangibles: theory, categories, and the Kozminski matrix. Knowledge Management Research & Practice, Vol. 11, pp. 101–111.

Spicer, J. (2005). Making sense of multivariate data analysis. Sage Publications,Inc. Thousand Oaks, California, the United States of America.

Statistics Finland. (2015a). A revised statistical standard industrial classification, TOL 2008, introduced in 2009. URL (last visited November 29, 2015): http://www.stat.fi/til/tol2008_en.html

Statistics Finland. (2015b). Trend Indicator of Output, 2015, September. URL (last visited November 29, 2015): http://www.tilastokeskus.fi/til/ktkk/2015/09/ktkk_2015_09_2015-11-13_en.pdf

Su, W. & Tsang, E.W.K. (2015). Product diversification and financial performance: The moderating role of secondary stakeholders. Academy of Management Journal, Vol. 58, No. 4, pp. 1128–1148.

Sveiby, K.E. (1997). The Intangible Assets Monitor. Journal of Human Resource Costing and Accounting, Vol. 2, No. 1, pp. 73–97.

Tanriverdi, H. & Venkatraman, N. (2005). Knowledge relatedness and the performance of multibusiness firms. Strategic Management Journal, Vol. 26, Iss. 2, pp. 97–119.

Teece, D.J., Pisano, G. & Shuen, A. (1997). Dynamic capabilities and strategic management. Strategic Management Journal, Vol. 18, Iss. 7, pp. 509–533.

Ting, I.W.K. & Lean, H.H. (2009). Intellectual capital performance of financial institutions in Malaysia. Journal of Intellectual Capital, Vol. 10, Iss. 4, pp. 588–599.

van Reijsen, J., Helms, R., Batenburg, R. & Foorthuis, R. (2015). The impact of knowledge management and social capital on dynamic capability in organizations. Knowledge Management Research & Practice, Vol. 13, Iss. 4, pp. 401–417.

Vidović, M. (2010). The link between the quality of knowledge management and financial performance – The case of Croatia. Faculty of Economics and Business – Zagreb. Working Paper Series. Paper No. 10-03.

Vinzi, V.E., Trinchera, L. & Amato, S. (2010). PLS path modeling: From foundations to recent developments and open issues for model assessment and improvement. Chapter 2. In: Vinzi, V.E., Chin, W.W., Henseler, J., Wang, H. (Eds.), Handbook of Partial Least Squares – Concepts, Methods and Applications. Springer Handbooks of Computational Statistics. Springer-Verlag, Berlin, Heidelberg. pp. 47–82.

Waddock, S.A. & Graves, S.B. (1997). The corporate social performance–financial performance link. Strategic Management Journal, Vol. 18, Iss. 4, 303–319.

Wiig, K. (1997). Integrating intellectual capital and knowledge management. Long Range Planning, Vol. 30, No. 3, pp. 399–405.

Zack, M.H. (1999). Developing a knowledge strategy. California Management Review, Vol. 41, No. 3, pp. 125–145.

Zhou, A.Z. & Fink, D. (2003). The intellectual capital web – A systematic linking of intellectual capital and knowledge management. Journal of Intellectual Capital, Vol. 4, Iss. 1, pp. 34–48.

BASIC COMPANY INFORMATION

JOBTITLE	**Your position at the company:** 1 = Managing director 2 = Manager or director responsible for human resources administration 3 = Other manager or director 4 = Expert or clerical employee 5 = Other, please specify: ____________
R&DSHARE	The proportion of research and development staff of all employees in 2012 (estimate of percentage between 0-100%)
PRODVSER	In 2012, our company's net sales consisted of: (1= Product sales/100%, 10 = Service sales/100%)
HIGHEDU	What proportion (to the nearest 10%) of your employees have: (A higher education degree, %)
NEWCEO	Has the managing director of your company changed during the past 24 months? (No = 0, Yes = 1)
NEWINCM	Has your company's primary source of revenue changed during the past 24 months? (No = 0, Yes = 1)
TANGBLTY	In your evaluation, to what extent do tangible resources (such as machinery, equipment and property) and intangible resources (such as knowledge, expertise, contacts and processes) represent the resources your company uses in its operations? (1 = operations are completely based on tangible resources, 10 = operations are completely based on intangible resources)

To what extent can the following be described as the sources of your company's competitiveness?
(1 = not at all, 5 = very much)

TACITK	Tacit knowledge and specialized expertise embedded in individuals and teams.
CODIFK	Documented knowledge and standardised expertise that can be replicated quickly and efficiently.

ORGANISATIONAL PERFORMANCE

Compared to other companies in its sector, how do you think your company has succeeded in the following areas over the past year?
(1 = very poorly, 5 = very well)

MARKPER1 Net sales growth
MARKPER2 Profitability
MARKPER3 Market share

Compared to its competitors, how successfully has your company managed to create innovations/new operating methods in the following areas over the past year?
(1 = very poorly, 5 = very well)

INNOPER1 Products and services for customers
INNOPER2 Production methods and processes
INNOPER3 Management practices
INNOPER4 Marketing practices
INNOPER5 Business models

Compared to other companies in its sector, how has your company succeeded in creating customer value over the past year?
(1 = very poorly, 5 = very well)

CUSTVAL1 Solving actual customer needs
CUSTVAL2 Producing benefits related to perceptions and emotions for customers in addition to solving actual customer needs
CUSTVAL3 Customer trust in your company's products, services and operations in general
CUSTVAL4 Responsiveness to enquiries and problems as experienced by customers
CUSTVAL5 Employees' professionalism and businesslike conduct as experienced by customers
CUSTVAL6 Care and individual attention as experienced by customers
CUSTVAL7 Value related to the display, tidiness and functionality of the company's products and services as experienced by customers

Evaluate the effect of your innovation operations on your company's net sales over the past year
(1 = no effect, 5 = significant positive effect)

INNORAD Entirely new products or services (radical innovation)
INNOINK Improved products or services (incremental innovation)

To what extent do the following statements on job satisfaction apply to your company?
(1 = completely disagree, 5 = completely agree)

JOBSAT1 Our employees are generally very satisfied with their jobs.
JOBSAT2 Most of our employees would like to switch to another company.
JOBSAT3 Our employees are generally very satisfied with their current duties.

INTELLECTUAL CAPITAL

To what extent do the following statements on internal cooperation apply to your company?
(1 = completely disagree, 5 = completely agree)

INTREL1	Different units and functions within our company – such as R&D, marketing and production – understand each other well.
INTREL2	Our employees frequently collaborate to solve problems.
INTREL3	Internal cooperation in our company runs smoothly.

To what extent do the following statements on external cooperation apply to your company?
(1 = completely disagree, 5 = completely agree)

EXTREL1	Our company and its external stakeholders – such as customers, suppliers and partners – understand each other well.
EXTREL2	Our company and its external stakeholders frequently collaborate to solve problems.
EXTREL3	Cooperation between our company and its external stakeholders runs smoothly.

To what extent do the following statements on internal structures apply to your company?
(1 = completely disagree, 5 = completely agree)

STRUCAP1	Our company has efficient and relevant information systems to support business operations.
STRUCAP2	Our company has tools and facilities to support cooperation between employees.
STRUCAP3	Our company has a great deal of useful knowledge in documents and databases.
STRUCAP4	Existing documents and solutions are easily accessible.

To what extent do the following statements on employee competence apply to your company?
(1 = completely disagree, 5 = completely agree)

HUMCAP1	Our employees are highly skilled at their jobs.
HUMCAP2	Our employees are highly motivated in their work.
HUMCAP3	Our employees have a high level of expertise.

To what extent do the following statements on renewal apply to your company?
(1 = completely disagree, 5 = completely agree)

RENCAP1	Our company has acquired a great deal of new and important knowledge.
RENCAP2	Our employees have acquired a great deal of important skills and abilities.
RENCAP3	Our company can be described as a learning organisation.
RENCAP4	The operations of our company can be described as creative and inventive.

To what extent do the following statements on trust apply to your company?
(1 = completely disagree, 5 = completely agree)

TRUSCAP1	The way our company operates is characterised by an atmosphere of trust.
TRUSCAP2	We keep our promises and agreements.
TRUSCAP3	Our company seeks to take the interests of its stakeholders into account in its operations.
TRUSCAP4	The expertise of our company inspires trust in stakeholders.
TRUSCAP5	The image and reputation of our company inspire trust in stakeholders.

To what extent do the following statements on the entrepreneurial orientation apply to your company?
(1 = completely disagree, 5 = completely agree)

ENTCAP1	Risk-taking is regarded as a positive personal quality in our company.
ENTCAP2	Our employees take deliberate risks related to new ideas.
ENTCAP3	Our employees are excellent at identifying new business opportunities.
ENTCAP4	Our employees show initiative.
ENTCAP5	The operations of our company are defined by independence and freedom in performing duties.
ENTCAP6	Our employees have the courage to make bold and difficult decisions.

KNOWLEDGE MANAGEMENT PRACTICES

To what extent do the following statements on supervisory work apply to your company?
(1 = completely disagree, 5 = completely agree)

KMLEAD1	Supervisors encourage employees to share knowledge at the workplace.
KMLEAD2	Supervisors encourage employees to question existing knowledge.
KMLEAD3	Supervisors allow employees to make mistakes, and they see mistakes as learning opportunities.
KMLEAD4	Supervisors value employees' ideas and viewpoints and take them into account.
KMLEAD5	Supervisors promote equal discussion in the workplace.
KMLEAD6	Supervisors share knowledge in an open and equal manner.
KMLEAD7	Supervisors continuously update their own knowledge.

To what extent do the following statements on knowledge protection apply to your company?
(1 = completely disagree, 5 = completely agree)

KPROT1	Our company's strategic knowledge is protected from those stakeholders to whom it is not intended.
KPROT2	If necessary, our company uses patents, agreements, legislation and other formal means to protect its strategic knowledge.
KPROT3	If necessary, our company uses confidentiality, employee guidance and other informal means to protect its strategic knowledge.

To what extent do the following statements on strategic knowledge and competence management apply to your company?
(1 = completely disagree, 5 = completely agree)

STRATKM1	Our company strategy is formulated and updated based on company knowledge and competences.
STRATKM2	Our company strategy addresses the development of knowledge and competences.
STRATKM3	Our company systematically compares its strategic knowledge and competence to that of its competitors.
STRATKM4	Our knowledge and competence management strategy is communicated to employees clearly and comprehensively.
STRATKM5	In our company, the responsibility for strategic knowledge management has been clearly assigned to a specific person.

To what extent do the following statements on human resources management apply to your company?
(1 = completely disagree, 5 = completely agree)

HRMREC1	When recruiting, we pay special attention to relevant expertise.
HRMREC2	When recruiting, we pay special attention to learning and development ability.
HRMREC3	When recruiting, we evaluate the candidates' ability to collaborate and work in various networks.
HRMTD1	We offer our employees opportunities to deepen and expand their expertise.
HRMTD2	We offer training that provides employees with up-to-date knowledge.
HRMTD3	Our employees have an opportunity to develop their competence through training tailored to their specific needs.
HRMTD4	Competence development needs of employees are discussed with them regularly.
HRMPAPP1	The sharing of knowledge is one of our criteria for work performance assessment.
HRMPAPP2	The creation of new knowledge is one of our criteria for work performance assessment.
HRMPAPP3	The ability to apply knowledge acquired from others is one of our criteria for work performance assessment.
HRMCOMP1	Our company rewards employees for sharing knowledge.
HRMCOMP2	Our company rewards employees for creating new knowledge.
HRMCOMP3	Our company rewards employees for applying knowledge.

To what extent do the following statements on learning practices apply to your company?
(1 = completely disagree, 5 = completely agree)

LRNMECH1	Our company transfers knowledge from experienced to inexperienced employees through mentoring, apprenticeship and job orientation, for example.
LRNMECH2	Our company systematically collects best practices and lessons learned.
LRNMECH3	Our company makes systematic use of best practices and lessons learned.

To what extent do the following statements on IT management practices apply to your company?
(1 = completely disagree, 5 = completely agree)

ITPRACT1	Our company uses information technology to enable efficient information search and discovery
ITPRACT2	Our company uses information technology in internal communication throughout the organisation.
ITPRACT3	Our company uses information technology to communicate with external stakeholders.
ITPRACT4	Our company uses information technology to analyse knowledge in order to make better decisions.
ITPRACT5	Our company uses information technology to collect business knowledge related to its competitors, customers and operating environment, for example.
ITPRACT6	Our company uses information technology to develop new products and services with external stakeholders.

To what extent do the following statements on organisation of work apply to your company?
(1 = completely disagree, 5 = completely agree)

WORKORG1	Our employees have an opportunity to participate in decision-making in the company.
WORKORG2	In our company, work duties are defined in a manner that allows for independent decision-making.
WORKORG3	We enable informal interaction between members of our organisation.
WORKORG4	Our company organises face-to-face meetings when necessary.
WORKORG5	When necessary, we use working groups with members who possess skills and expertise in a variety of fields.
WORKORG6	When needed, our company makes use of various expert communities.

Appendix 2a

Item	KM	IC	OP
HRMCOMP1	0.55	.	.
HRMCOMP2	0.54	.	.
HRMCOMP3	0.56	.	.
HRMPAPP1	0.63	.	.
HRMPAPP2	0.55	.	.
HRMPAPP3	0.62	.	.
HRMREC1	0.47	0.40	.
HRMREC2	0.51	0.45	.
HRMREC3	0.60	.	.
HRMTD1	0.62	0.55	.
HRMTD2	0.68	0.58	.
HRMTD3	0.62	.	.
HRMTD4	0.63	.	.
ITPRACT1	0.55	0.48	.
ITPRACT2	0.51	.	.
ITPRACT3	0.45	0.38	.
ITPRACT4	0.50	.	.
ITPRACT5	0.52	.	.
ITPRACT6	0.46	.	.
KMLEAD1	0.69	0.60	.
KMLEAD2	0.60	0.56	.
KMLEAD3	0.55	0.55	.
KMLEAD4	0.65	0.65	.
KMLEAD5	0.64	0.59	.
KMLEAD6	0.58	0.51	.
KMLEAD7	0.66	0.63	.
KPROT1	0.43	0.40	.
KPROT2	0.43	.	.
KPROT3	0.46	.	.
LRNMECH1	0.51	0.43	.
LRNMECH2	0.63	.	.
LRNMECH3	0.68	0.55	.
STRATKM1	0.60	.	.
STRATKM2	0.62	.	.
STRATKM3	0.47	.	.
STRATKM4	0.59	.	.
STRATKM5	0.46	.	.
WORKORG1	0.53	.	.
WORKORG2	0.61	0.55	.
WORKORG3	0.60	0.55	.
WORKORG4	0.58	.	.
WORKORG5	0.47	.	.
WORKORG6	0.55	.	.
ENTCAP1	.	0.53	.
ENTCAP2	0.54	0.60	.
ENTCAP3	0.56	0.65	.
ENTCAP4	.	0.63	.
ENTCAP5	.	0.55	.
ENTCAP6	0.60	0.72	.
EXTREL1	.	0.46	.
EXTREL2	0.45	0.53	.
EXTREL3	.	0.57	.
HUMCAP1	.	0.56	.
HUMCAP2	0.58	0.64	.
HUMCAP3	.	0.65	.
INTREL1	.	0.45	.
INTREL2	.	0.63	.
INTREL3	.	0.57	.
RENCAP1	0.53	0.63	.
RENCAP2	0.57	0.67	.
RENCAP3	0.65	0.73	.
RENCAP4	.	0.71	.
STRUCAP1	.	0.41	.
STRUCAP2	0.41	0.48	.
STRUCAP3	0.41	0.47	.
STRUCAP4	0.45	0.49	.
TRUSCAP1	.	0.69	.
TRUSCAP2	0.54	0.60	.
TRUSCAP3	0.47	0.57	.
TRUSCAP4	0.50	0.62	.
TRUSCAP5	.	0.59	.
ROA2014	.	.	1.00

Appendix 2b

Item	KM	IC	OP
HRMCOMP1	0.53	.	.
HRMCOMP2	0.52	.	.
HRMCOMP3	0.54	.	.
HRMPAPP1	0.63	.	.
HRMPAPP2	0.58	.	.
HRMPAPP3	0.6	.	.
HRMREC1	0.51	0.43	.
HRMREC2	0.53	0.44	.
HRMREC3	0.59	.	.
HRMTD1	0.62	0.54	.
HRMTD2	0.67	0.56	.
HRMTD3	0.6	.	.
HRMTD4	0.61	.	.
ITPRACT1	0.56	0.49	.
ITPRACT2	0.51	.	.
ITPRACT3	0.42	0.37	.
ITPRACT4	0.49	.	.
ITPRACT5	0.5	.	.
ITPRACT6	0.46	.	.
KMLEAD1	0.7	0.61	.
KMLEAD2	0.61	0.56	.
KMLEAD3	0.57	0.56	.
KMLEAD4	0.66	0.66	.
KMLEAD5	0.65	0.58	.
KMLEAD6	0.57	0.52	.
KMLEAD7	0.64	0.62	.
KPROT1	0.43	0.41	.
KPROT2	0.41	.	.
KPROT3	0.47	0.39	.
LRNMECH1	0.5	.	.
LRNMECH2	0.63	.	.
LRNMECH3	0.67	0.55	.
STRATKM1	0.59	.	.
STRATKM2	0.64	.	.
STRATKM3	0.46	.	.
STRATKM4	0.57	.	.
STRATKM5	0.43	.	.
WORKORG1	0.5	.	.
WORKORG2	0.6	0.54	.
WORKORG3	0.6	0.56	.
WORKORG4	0.58	.	.
WORKORG5	0.44	.	.
WORKORG6	0.54	.	.
ENTCAP1	.	0.52	.
ENTCAP2	0.53	0.6	.
ENTCAP3	0.55	0.65	.
ENTCAP4	0.5	0.61	.
ENTCAP5	.	0.55	.
ENTCAP6	0.58	0.71	.
EXTREL1	.	0.43	.
EXTREL2	0.45	0.52	.
EXTREL3	.	0.55	.
HUMCAP1	.	0.58	.
HUMCAP2	0.58	0.66	.
HUMCAP3	.	0.65	.
INTREL1	.	0.46	.
INTREL2	.	0.65	.
INTREL3	.	0.57	.
RENCAP1	0.55	0.63	.
RENCAP2	0.59	0.67	.
RENCAP3	0.64	0.73	.
RENCAP4	.	0.7	.
STRUCAP1	0.35	0.43	.
STRUCAP2	0.41	0.49	.
STRUCAP3	0.42	0.47	.
STRUCAP4	0.48	0.5	.
TRUSCAP1	.	0.68	.
TRUSCAP2	0.54	0.6	.
TRUSCAP3	.	0.56	.
TRUSCAP4	0.54	0.64	.
TRUSCAP5	.	0.61	.
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Complete data
n = 227

Item	Minimum	Mean	Median	Maximum	Standard deviation
KMLEAD	-0.06	-0.016	-0.020	0.07	0.051
KPROT	-0.07	0.040	0.040	0.15	0.110
STRATKM	-0.03	0.050	0.060	0.12	0.060
HRMPRACT	-0.06	0.069	0.120	0.16	0.075
LRNMECH	0.08	0.097	0.100	0.11	0.015
ITPRACT	0.00	0.063	0.075	0.11	0.047
WORKORG	-0.02	0.048	0.010	0.17	0.077
INTREL	-0.01	0.013	0.010	0.04	0.025
EXTREL	0.11	0.130	0.120	0.16	0.026
STRUCAP	-0.09	-0.017	-0.015	0.05	0.057
HUMCAP	-0.01	0.047	0.020	0.13	0.074
RENCAP	0.03	0.042	0.040	0.06	0.015
TRUSCAP	0.02	0.054	0.060	0.09	0.029
ENTCAP	-0.04	0.010	0.010	0.08	0.039

TOL2008-classes 1, 2, 3, 4, 5, and 8
n = 119

Item	Minimum	Mean	Median	Maximum	Standard deviation
KMLEAD	-0.11	-0.016	-0.020	0.08	0.063
KPROT	-0.08	0.023	0.020	0.13	0.105
STRATKM	-0.06	0.018	0.010	0.14	0.079
HRMPRACT	-0.04	0.030	0.040	0.15	0.062
LRNMECH	0.10	0.113	0.100	0.14	0.023
ITPRACT	0.01	0.083	0.080	0.16	0.061
WORKORG	-0.06	0.012	0.010	0.09	0.052
INTREL	0.01	0.063	0.070	0.11	0.050
EXTREL	0.07	0.140	0.160	0.19	0.062
STRUCAP	-0.10	0.010	0.035	0.07	0.078
HUMCAP	-0.01	0.050	0.000	0.16	0.095
RENCAP	-0.07	-0.010	0.000	0.03	0.043
TRUSCAP	-0.11	0.012	0.000	0.16	0.107
ENTCAP	-0.08	-0.018	-0.025	0.03	0.043

TOL2008-classes 6 and 7
n = 108

Item	Minimum	Mean	Median	Maximum	Standard deviation
KMLEAD	-0.10	-0.014	0.000	0.04	0.054
KPROT	-0.05	0.073	0.100	0.17	0.112
STRATKM	-0.01	0.086	0.090	0.18	0.068
HRMPRACT	-0.08	0.119	0.150	0.24	0.111
LRNMECH	0.05	0.070	0.070	0.09	0.020
ITPRACT	-0.05	0.035	0.060	0.08	0.057
WORKORG	-0.03	0.083	0.030	0.30	0.122
INTREL	-0.05	-0.033	-0.040	-0.01	0.021
EXTREL	0.06	0.113	0.110	0.17	0.055
STRUCAP	-0.10	-0.048	-0.065	0.04	0.062
HUMCAP	-0.03	0.040	0.060	0.09	0.062
RENCAP	0.07	0.090	0.085	0.12	0.022
TRUSCAP	-0.04	0.114	0.130	0.22	0.107
ENTCAP	-0.06	0.043	0.045	0.14	0.079

$N_{\text{employees}} < 200$
$n = 114$

Item	Minimum	Mean	Median	Maximum	Standard deviation
KMLEAD	-0.15	-0.099	-0.110	0.00	0.049
KPROT	-0.12	-0.007	-0.020	0.12	0.121
STRATKM	-0.22	-0.060	-0.070	0.06	0.107
HRMPRACT	-0.18	0.003	0.040	0.16	0.099
LRNMECH	-0.05	-0.013	0.000	0.01	0.032
ITPRACT	-0.13	-0.045	-0.040	0.05	0.073
WORKORG	-0.08	0.017	-0.035	0.20	0.109
INTREL	-0.11	-0.070	-0.060	-0.04	0.036
EXTREL	0.01	0.063	0.090	0.09	0.046
STRUCAP	-0.16	-0.082	-0.105	0.04	0.090
HUMCAP	-0.14	-0.057	-0.050	0.02	0.080
RENCAP	-0.03	0.000	0.005	0.02	0.022
TRUSCAP	-0.03	0.046	0.020	0.12	0.062
ENTCAP	-0.11	-0.017	0.010	0.03	0.059

$N_{\text{employees}} \geq 200$
$n = 113$

Item	Minimum	Mean	Median	Maximum	Standard deviation
KMLEAD	-0.04	0.049	0.040	0.21	0.089
KPROT	-0.04	0.063	0.070	0.16	0.100
STRATKM	0.06	0.138	0.140	0.21	0.055
HRMPRACT	-0.01	0.124	0.140	0.23	0.071
LRNMECH	0.17	0.197	0.200	0.22	0.025
ITPRACT	0.12	0.152	0.145	0.21	0.034
WORKORG	0.00	0.072	0.060	0.14	0.059
INTREL	0.02	0.077	0.060	0.15	0.067
EXTREL	0.11	0.170	0.200	0.20	0.052
STRUCAP	-0.03	0.042	0.050	0.10	0.054
HUMCAP	0.07	0.117	0.080	0.20	0.072
RENCAP	0.02	0.065	0.070	0.10	0.037
TRUSCAP	-0.05	0.052	0.030	0.14	0.081
ENTCAP	-0.01	0.025	0.000	0.12	0.050

Complete data
n = 214

Item	Minimum	Mean	Median	Maximum	Standard deviation
KMLEAD	-0.10	-0.009	-0.010	0.08	0.056
KPROT	0.03	0.077	0.100	0.10	0.040
STRATKM	-0.04	0.030	0.020	0.11	0.068
HRMPRACT	-0.03	0.059	0.060	0.15	0.046
LRNMECH	0.08	0.110	0.120	0.13	0.026
ITPRACT	0.02	0.070	0.065	0.15	0.049
WORKORG	-0.06	0.020	0.015	0.09	0.054
INTREL	0.04	0.100	0.110	0.15	0.056
EXTREL	0.08	0.083	0.080	0.09	0.006
STRUCAP	-0.05	0.010	0.005	0.08	0.055
HUMCAP	0.01	0.070	0.040	0.16	0.079
RENCAP	0.03	0.053	0.055	0.07	0.017
TRUSCAP	-0.01	0.064	0.060	0.14	0.062
ENTCAP	-0.04	-0.003	-0.015	0.07	0.040

TOL2008-calsses 1, 2, 3, 4, 5, and 8
n = 112

Item	Minimum	Mean	Median	Maximum	Standard deviation
KMLEAD	-0.02	0.099	0.100	0.18	0.067
KPROT	0.03	0.087	0.110	0.12	0.049
STRATKM	-0.10	0.074	0.090	0.20	0.122
HRMPRACT	0.00	0.112	0.110	0.18	0.054
LRNMECH	0.13	0.197	0.220	0.24	0.059
ITPRACT	0.05	0.157	0.155	0.25	0.076
WORKORG	-0.02	0.103	0.130	0.17	0.069
INTREL	0.17	0.200	0.210	0.22	0.026
EXTREL	0.15	0.200	0.200	0.25	0.050
STRUCAP	0.05	0.105	0.100	0.17	0.064
HUMCAP	0.03	0.087	0.040	0.19	0.090
RENCAP	0.08	0.112	0.115	0.14	0.025
TRUSCAP	-0.08	0.076	0.080	0.22	0.120
ENTCAP	-0.01	0.072	0.075	0.15	0.052

TOL2008-calsses 6 and 7
n = 102

Item	Minimum	Mean	Median	Maximum	Standard deviation
KMLEAD	-0.18	-0.126	-0.130	-0.05	0.042
KPROT	0.05	0.093	0.070	0.16	0.059
STRATKM	-0.08	0.000	0.010	0.06	0.060
HRMPRACT	-0.14	0.017	0.020	0.13	0.070
LRNMECH	0.01	0.020	0.020	0.03	0.010
ITPRACT	-0.11	-0.020	-0.025	0.08	0.063
WORKORG	-0.12	-0.062	-0.085	0.05	0.062
INTREL	-0.06	0.010	0.000	0.09	0.075
EXTREL	-0.09	-0.030	-0.050	0.05	0.072
STRUCAP	-0.15	-0.092	-0.105	-0.01	0.059
HUMCAP	-0.01	0.050	0.040	0.12	0.066
RENCAP	-0.04	-0.020	-0.030	0.02	0.027
TRUSCAP	-0.04	0.058	0.060	0.19	0.086
ENTCAP	-0.15	-0.063	-0.055	-0.01	0.050

$N_{employees} < 200$
$n = 109$

Item	Minimum	Mean	Median	Maximum	Standard deviation
KMLEAD	-0.26	-0.160	-0.160	-0.12	0.050
KPROT	-0.07	-0.063	-0.070	-0.05	0.012
STRATKM	-0.28	-0.164	-0.160	-0.07	0.077
HRMPRACT	-0.20	-0.074	-0.040	0.03	0.072
LRNMECH	-0.12	-0.113	-0.110	-0.11	0.006
ITPRACT	-0.13	-0.085	-0.105	-0.02	0.044
WORKORG	-0.21	-0.063	-0.055	0.04	0.081
INTREL	-0.07	-0.003	-0.020	0.08	0.076
EXTREL	-0.13	-0.083	-0.060	-0.06	0.040
STRUCAP	-0.18	-0.118	-0.145	0.00	0.080
HUMCAP	-0.18	-0.107	-0.170	0.03	0.118
RENCAP	-0.14	-0.132	-0.130	-0.13	0.005
TRUSCAP	-0.10	-0.020	0.000	0.04	0.058
ENTCAP	-0.14	-0.100	-0.120	-0.03	0.048

$N_{employees} \geq 200$
$n = 105$

Item	Minimum	Mean	Median	Maximum	Standard deviation
KMLEAD	0.01	0.080	0.050	0.22	0.073
KPROT	0.10	0.160	0.180	0.20	0.053
STRATKM	0.04	0.158	0.150	0.26	0.081
HRMPRACT	0.02	0.149	0.140	0.28	0.068
LRNMECH	0.20	0.257	0.280	0.29	0.049
ITPRACT	0.12	0.170	0.140	0.28	0.063
WORKORG	0.02	0.073	0.060	0.15	0.052
INTREL	0.10	0.163	0.190	0.20	0.055
EXTREL	0.17	0.190	0.180	0.22	0.026
STRUCAP	0.00	0.082	0.095	0.14	0.060
HUMCAP	0.12	0.177	0.180	0.23	0.055
RENCAP	0.14	0.168	0.165	0.20	0.028
TRUSCAP	0.02	0.114	0.070	0.25	0.097
ENTCAP	-0.04	0.053	0.050	0.20	0.088