Exploratory Study of Societal Contexts and Industry Performance

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ABSTRACT

There is inconclusive evidence on the effectiveness of information and communication technologies (ICT) at the industry level. Using the influence-impact model as a theoretical framework, the authors apply data mining techniques to identify ICT, financial, and geographical predictors of industry performance. The authors find that ICT are necessary but insufficient, and a mix of technical advancement, financial factors, and geography affect industry performance at different stages of development. These findings are used to discuss ICT for development (ICT4D) research, and abduct hypotheses for theory development with implications for future research.

KEYWORDS

Abduction, ICT, ICT4D, Influence Impact Model, Manufacturing Industries, Performance

INTRODUCTION

ICT are synonymous with information systems (IS) and information technology (IT) (Schryen, 2013). They spur growth and development in developed and developing countries (Appiah-Otoo & Song, 2021) toward digital economies by improving performance, competitiveness (Koivunen et al., 2008), welfare, and network externalities (Torero & Von Braun, 2006). However, studies find their ability to improve productivity, growth, and other performance indicators (Bloom et al., 2010; Botello & Pedraza Avella, 2014), inconsistent (Piget & Kossaï, 2013). Firm-level ICT impact is mostly positive (Chipidza & Leidner, 2019) but inconsistent at the industry level (Devaraj & Kohli, 2000; Schryen, 2013), warranting more industry research (Chae et al., 2018; Crowston & Myers, 2004). This is because technologies are tied to their contexts (Cutrell, 2011; Pacey, 1983), causing ICT to have different impact under different conditions. Contexts add rigor to research findings, and their absence diminishes our understanding of ICT impact (Ko & Osei-Bryson, 2004; Yeo & Grant, 2019b). ICT4D research is also insufficiently grounded in theory (Heffernan et al., 2016; Sein et al., 2019), and Karanasios (2014) recommends rigorous theoretical approaches to interpret and unify ICT4D research.

Despite a need for ICT4D researchers to develop hypotheses and analytical directions (Avgerou, 2017), researchers face challenges developing new, rigorous, and relevant knowledge on existing and emerging problems (Osei-Bryson & Ngwenyama, 2011) to expand theories, identify alternate

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explanations (Popper, 1957), new hypotheses (Popper, 1959), and advance theoretical contributions (Popper, 2014). Osei-Bryson and Ngwenyama (2014) acknowledge generating hypotheses for empirical testing is a persistent IS challenge of emerging technologies and dynamic organizations. This is compounded by the lack of technical aids and can be overcome by abducting hypotheses using data mining (Osei-Bryson & Ngwenyama, 2011).

Motivated by these challenges, the objectives of this exploratory study are 1. to use a contextual theory to investigate how societal contexts and ICT influence industry performance, and 2. to abduct testable propositions and hypotheses for future ICT4D research. We use the Influence-Impact Framework (IIF) to develop a hybrid data mining method for this exploratory research (Osei-Bryson & Ngwenyama, 2011) on ICT impact. The findings inform technology-driven development in developing countries and illustrate how IIF can be used to study ICT4D. We use three overarching research questions for this investigation:

Research Question One (RQ1): How does infrastructure affect manufacturing industries sales growth?
Research Question One (RQ2): How does economy affect manufacturing industries sales growth?
Research Question One (RQ3): How does culture affect manufacturing industries sales growth?

The results are used to generate propositions (Xue et al., 2008) and hypotheses (Fann, 2012; Osei-Bryson & Ngwenyama, 2011) for future ICT4D research. This process of abduction departs from traditional deductive and inductive approaches (Osei-Bryson & Ngwenyama, 2011). We hope the new hypotheses lead to new knowledge that supports ICT industry growth and business decisions.

The remainder of the paper is organized as follows: The Literature Review discusses ICT impact on performance and the IIF research model for the study. The Research Method describes the steps, the data, and our use of clustering and decision trees to construct a hybrid data mining method. Clustering identifies distinct industry groups and decision trees identify the predictors that drive industry performance in each. The Results and Explanation section discuss the findings, which are then used in the Discussion and Conclusion to develop propositions and hypotheses for new knowledge creation, discuss the research contributions, theoretical and policy implications, and limitations.

LITERATURE REVIEW

ICT4D definitions of development vary widely (Thapa & Sæbø, 2014; Walsham, 2013) and include, but not limited to increased freedom, expanded inclusion, increased economic productivity (Gordon & Sayed, 2020), and improved well-being (Chipidza & Leidner, 2019). Increased freedom refers to expanded liberties enjoyed by ICT beneficiaries (Sen, 1999). Expanded inclusion enables the disenfranchised to gain access to ICT (Madon et al., 2009). Economic productivity is measured GDP, business performance, employment and output (Chipidza & Leidner, 2019). Improved well-being includes ICT-driven satisfaction, happiness, and fulfilment (Ganju et al., 2015). This study is premised on economic productivity and investigates ICT impact on global industry performance, a challenging task (Chipidza & Leidner, 2019).

ICT Impact is Inconsistent

ICT4D studies demonstrate positive economic ICT impact (Chipidza & Leidner, 2019) and ICT experiences differ among countries (Al-Hujran et al., 2018). ICT enable networking, information access, communication, increase societal participation, social standing, reduce social exclusion, physical barriers, research and development (Koutroumpis et al., 2020), economic growth (Appiah-Otoo & Song, 2021; Farouq et al., 2020; Liao et al., 2015; Vu et al., 2020), increase capacity utilization (Yeo & Grant, 2019a), productivity (Asongu & Acha-Anyi, 2020;

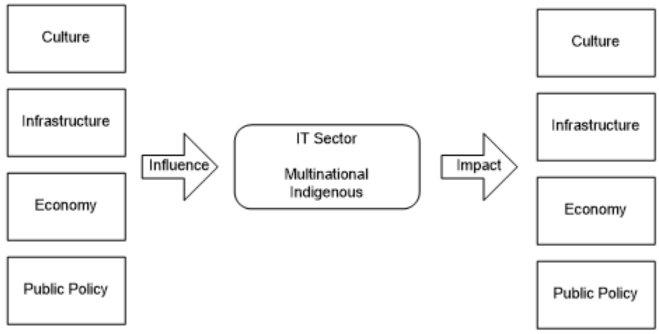
Koutroumpis et al., 2020), sales growth (Grant & Yeo, 2018b; Yeo & Grant, 2018, 2019b), and firm performance (Chae et al., 2018). They reduce labor cost (Fung, 2008), increase jobs, innovation, and competitiveness (Torero & Von Braun, 2006). However, ICT industry and country impact are inconsistent (Schryen, 2013) and contradictory (Ho et al., 2011; Motiwalla et al., 2005). For example, Jorgenson and Stiroh (2000) find ICT improve productivity, but previously did not (Jorgenson & Stiroh, 1995). Some recent studies show evidence of ICT impact on U.S. firm performance while earlier ones did not (Bloom et al., 2010). ICT infrastructure improves performance in West Africa (Bollou, 2006), and economic growth (Lee et al., 2005), but Jacobsen (2003) found otherwise. ICT impact also differs by region as the U.S. is more productive than Europe, due to early adoption, institutional differences (Matteucci et al., 2005), and country infrastructure (Bollou, 2006). ICT significantly boosts GDP in Asian and OECD countries and affect trade in Africa (Bankole et al., 2015), but have negatively affected sub-Saharan Africa (Guitat & Drine, 2007), and less effective in developing countries (World Development Report 2016: Digital Dividends, 2016). However, recent evidence suggests poorer countries benefit more from ICT impact than richer countries (Appiah-Otoo & Song, 2021).

These conflicting results suggest ICT impact is contextual (Schryen, 2013), and depends on many factors like industry type (Chae et al., 2018), investment levels (Ho et al., 2017), financial factors (Chae et al., 2018; Yeo & Grant, 2019b), job training and education (Dearden et al., 2006; Dedrick et al., 2011), infrastructure capabilities (Bollou, 2006; Schryen, 2013), income, wealth, digital divide, and geography (Torero & Von Braun, 2006; Yeo & Grant, 2019b), and relate to a country's history, governance (Walsham, 2017), tourism and culture (Zhou & Sotiriadis, 2021). These contextual factors explain ICT-driven performance (Richardson & Zmud, 2002).

Influence-Impact Framework

The Influence-Impact Framework (IIF) addresses inconsistencies by using four societal contexts – infrastructure, public policy, economic, and culture – that influence IT-driven industry and economic development (Trauth, 2000) (Figure 1). They are often absent in ICT studies (Weisinger & Trauth, 2002) to analyze, interpret, and explain ICT results. The contexts on the left influence the IT sector, which influence those on the right (Trauth, 2000). An IT sector comprises industries that produce software, hardware, semiconductor equipment, and internet services. Contexts give meaning to discussions, measurement targets, and provide theories for explaining and interpreting results. Culture comprises evolving beliefs, values, and norms that influence business strategy, management, decision-making, and they vary across countries (Hofstede, 1980). Hofstede compares cultures across countries (Palvia et al., 2017), allowing culture to represent geography. Culture and geography are inextricably linked by cultural geography (Jordan-Bychkov, 2005), which focuses on patterns of human culture and behavior. Economy encompasses the production, distribution, and consumption of goods

Figure 1. Influence-Impact Model of the information economy



and services. Public policy includes principles that shape societal laws. Infrastructure is hardware, data centers, software, networks, and equipment to store, process, disseminate, and support ICT. IIF defines infrastructure as both IT and human infrastructure (users).

Applying the Influence-Impact Framework

We focus on three IIF contexts – infrastructure, economy, and culture – to answer our three research questions. They are operationalized by ICT, financial factors (interest rates, bank bureaucracies, collateral requirements, and access to financing) as economic indicators (Beck et al., 2005), and country respectively. Different countries have different cultures (Hofstede, 1980) with their unique business practice, and tourism (Zhou & Sotiriadis, 2021). Cultural geography links country and culture by identifying similar cultures separated by geography (Jordan-Bychkov, 2005). Human infrastructure and public policy contexts are outside the research scope and there is precedence in omitting them (Trauth, 1999; Trauth et al., 2008; Weisinger & Trauth, 2002; Yeo & Trauth, 2004).

RESEARCH METHOD

The research method has three steps (Figure 2):

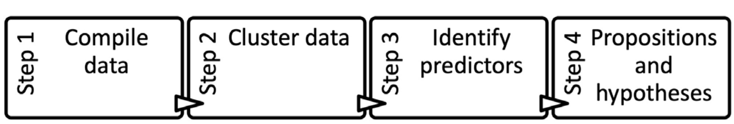
Step 1: We obtained industry data on variables that operationalize the three IIF contexts: infrastructure, economy, and culture.
Step 2: We used k-means clustering to identify four technologically advanced industry groups, using twelve variables from infrastructure and economy. The optimal number of groups were identified using the silhouette measure, as the cluster quality criterion. A higher silhouette measure indicates better cluster quality.
Step 3: We explored predictors of industry performance for each industry group, using DT induction.
Step 4: We used the results from Step 3 to abduct propositions, hypotheses, and new theory for future ICT4D research.

Data, Variables, and Conceptual Research Model

The need for more industry research (Chae et al., 2018; Crowston & Myers, 2004) is accomplished by using a World Bank industry dataset, compiled from a survey of 135 countries (cf. Appendix) between 2006 to 2015. It includes 29 manufacturing industries in Central, and South America, Africa, Asia, Eastern, and Western Europe. The unit of analysis is a record that represents an industry-country-year, hence, a record from the machinery and equipment industry in Ukraine in 2013, differs from the machinery and equipment industry record in Sweden in 2014. Industries are unequally represented across countries, and countries do not have an equal number of yearly records. Despite the limitations, access to extensive data covering many developing countries benefits researchers and practitioners as implications are relevant to industries at different development stages. Less advanced learn from the advanced industries and the IIF contexts are relevant to industries.

Industry annual sales growth represents industry performance, the target variable (Grant & Yeo, 2018b; Yeo & Grant, 2019b). For the decision tree induction, we converted industry sales growth to a categorical variable with two outcomes: industry records with positive and negative growth are

Figure 2. Method steps



recoded as positive and negative respectively. Figure 3 shows our research model adapted from the IIF, with three societal contexts representing ICT impact (RQ1), financial factors (RQ2), and geography (RQ3) on industry annual sales growth.

The five ICT infrastructure predictors (Table 1) that operationalize ICT use, come from the technology and innovation section of the survey. Table 1 includes the three contexts and 13 infrastructure, economy, and geography variables. An industry is comprised of firms, and each industry-country-year record has values for these variables. Internationally recognized quality certifications require technology for compliance, data storage, processing, quality assurance, security, auditing, and report generation. Foreign country-licensed technologies are productivity software not obtained locally. External audits require technologies for compliance. Constrained by the available survey variables, these five predictors operationalize the infrastructure context. The relationship between manufacturing sales revenue and financial factors is a viable research problem (Yeo & Grant, 2019b). The dataset has 15 economy variables that were reduced to seven using six performance constraints (Beck et al., 2005) to simplify interpretation (Shmueli et al., 2017). Performance and growth are constrained by 1. Connections with banks; 2. Banks' lack of money; 3. High interest rates; 4. Banking bureaucracies; 5. Collateral requirements; 6. Lack of financing access. Collateral requirements are the proportion of loans requiring collateral and collateral value (Beck et al., 2005). These constraints relate to seven variables in the dataset: interest rates, bureaucracy, and financing access relate to the percent of firms with a bank loan/line of credit, proportion of investments financed by banks, proportion of supplier credit investment, and proportion of equity or stock sales investments. Bureaucracy, interest rates, collateral requirements, or lack of financing access are the proportion of equity or stock sales investments, and the proportion of working capital financed by supplier credit.

Figure 3. Research model

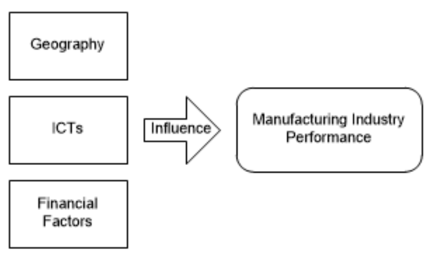


Table 1. Summary of variables

Construct	Variables (Predictors) of the model
Infrastructure	• Internationally recognized quality certification • Use of foreign country-licensed technology • Available company website • Email communication usage • External audits
Economy	• Percent of companies with a bank loan/line of credit • Proportion of loans requiring collateral • Value of collateral needed for a loan (Percent of the loan amount) • Proportion of investments financed by banks • Proportion of investments financed by supplier credit • Proportion of investments financed by equity or stock sales • Proportion of working capital financed by supplier credit
Culture	• Geographical region

Geography represents the country for each industry-country-year record and the IIF cultural context, because each country has its own cultural traits (Hofstede, 1980). Cultural diversity reflects organizations' adaption of standards, practices, ICT use (Markus et al., 2000; Walsham, 2001; Weisinger & Trauth, 2002), products, and services of a non-monolithic global IT industry.

Use of Clustering and Decision Tree Induction

Clustering classifies data into homogeneous groups, enabling sales growth analysis using different classification rules for different groups. The hybrid method produces a richer analysis (Osei-Bryson & Ngwenyama, 2014), akin to market segmentation followed by different targeted marketing strategies (Liu et al., 2019). Twelve variables from infrastructure and economy were used to group the data into distinct industries for DT induction. Geographical region (country), a categorical variable, was excluded from the clustering. We selected k-means clustering because it is often used and preferred over less stable hierarchical clustering (Shmueli et al., 2017), which is hard to interpret for larger datasets. Each cluster of industry-country-year records shares similar characteristics within cluster (cohesion), and dissimilarities across clusters (separation), reflecting the overall cluster quality (Osei-Bryson & Ngwenyama, 2014).

Decision trees are used in medicine (Kobayashi et al., 2013; Rodríguez et al., 2016), marketing (Amir et al., 2015; Díaz-Pérez & Bethencourt-Cejas, 2016), yet seldom used in mainstream IS research (Osei-Bryson & Ngwenyama, 2014) to identify classification rules from predictors (Tomic Rotim et al., 2013). However, they are more accurate than traditional statistical techniques in financial analyses (Barboza et al., 2017). Decision trees classify (Osei-Bryson, 2004; Wang et al., 2006) and analyze non-linear relationships between predictors and the target variable (Pal & Mather, 2003) by splitting data using conditions, and require no data distribution assumptions. They process both categorical and numerical variables and show the range of variable values in the classification. Decision tree classification rules vary for different segments of a dataset, making it difficult to identify underlying relationships. Their visual representation is easy to interpret (Murphy & Comiskey, 2013). We use CHAID DT to identify important variables (predictors) and classification rules that influence annual sales growth. They are then used to abduct propositions and hypotheses for future research. The tree depth was limited to 3 to avoid overfitting, and each parent and child node to a minimum of 2% and 1% of the records, respectively.

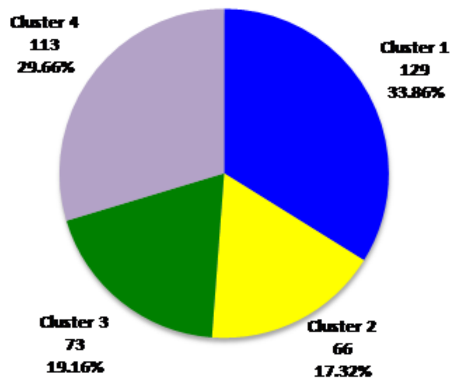
Many ICT4D studies use qualitative, interpretive methods (Lin et al., 2015), but quantitative studies have advantages in identifying statistical relationships among variables. Data mining is seldom used in IS research but appropriate for exploratory studies because it involves inductive, data-centric methods to test and develop theories (Osei-Bryson & Ngwenyama, 2014). The empirical findings are used to generate testable hypotheses and theory to improve IS research (Osei-Bryson & Ngwenyama, 2011), specifically ICT4D.

RESULTS AND EXPLANATION

Descriptive and Clustering Analysis

To acquire high quality clusters with manageable results that are easily interpreted, we use the silhouette statistic (s) to represent cluster quality (Rousseeuw, 1987) and is superior to arbitrarily defining clusters. We varied k between 2 and 6 and measured s to achieve the best cluster quality at $s = 0.3$ for $k = 4$ (Figure 4). Cluster 2, the biggest user of email at 92.71%, websites use at 64.22%, and the biggest user of bank loan or line of credit at 61.27%. Cluster 3 is next with 80.87% email use, 57.07% website use, and 27.83% use of bank loan/line of credit. Third, is Cluster 4 with 79.64% email use, 41.86% website use, and 44.73% bank loan/line of credit, and last is Cluster 1 with 30.55% email use, 14.72% website use, and 16.64% bank loan/line of credit. For the percent of firms with internationally recognized quality certifications, Cluster 1 has the lowest mean of 8.49% and clusters

Figure 4. Cluster sizes



3, 2 and 4 with higher means of 42.34%, 25.67%, and 16.68% respectively. Pertaining to the percent of firms with an annual financial statement reviewed by external auditors, Cluster 1 has a very low mean (0.25%) and Clusters 3, 4 and 2 with higher means of 68.39%, 54.21%, and 44.60% respectively.

Table 2 shows Cluster 3 is the most technologically advanced, followed by 2, 4, and 1. Cluster 1 is the only cluster with a negative mean sales growth of -1.02%. Clusters 2, 4, and 3 have the highest mean annual sales growth at 9.31%, 7.03%, and 4.58% respectively, as ICT correlate to stronger sales growth.

Decision Tree Induction

We built four CHAID DT – one for each cluster – using the predictors from the economy, infrastructure, and cultural contexts. Sales growth was computed as a binary variable with 2 levels representing positive and negative growth.

Cluster 1

The DT prediction accuracy of Cluster 1 sales growth is 75.97% and top five predictors in descending order (Figure 5), and DT tree (Figure 6). The percent of firms using technology licensed from foreign companies is the most important predictor. The top split includes industries with more than zero but less than or equal to 4.60%, and those with more than 4.60% using technology licensed from foreign companies.

In the first branch, industries with less than or equal to 4.60% of technology licensed from foreign companies exhibit negative growth ($\chi^2 = 57.794$, $p<0.001$). In this subset of industries, those with less than or equal to 7.90% of firms using email to communicate with clients and suppliers exhibit positive growth, while those with more than 7.90% exhibit negative growth ($\chi^2 = 11.717$, $p=0.023$). While the split in this branch is based on technology licensed from foreign companies suggests

Table 2. Cluster descriptions

Cluster	Average of ICT	Average of Finance
1	18.41	29.06
2	47.93	45.50
3	53.67	39.82
4	41.22	47.32

Figure 5. Predictor importance in cluster 1

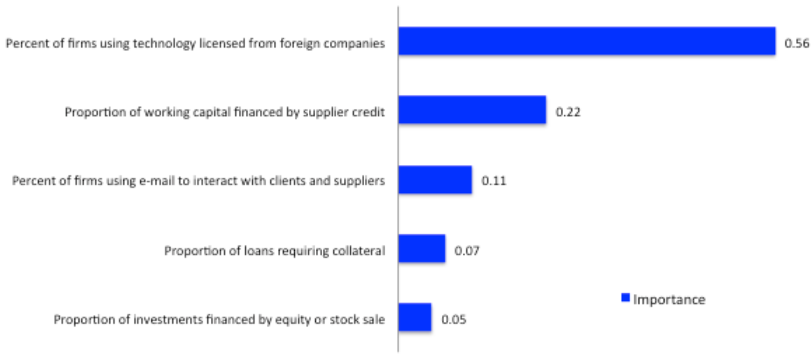
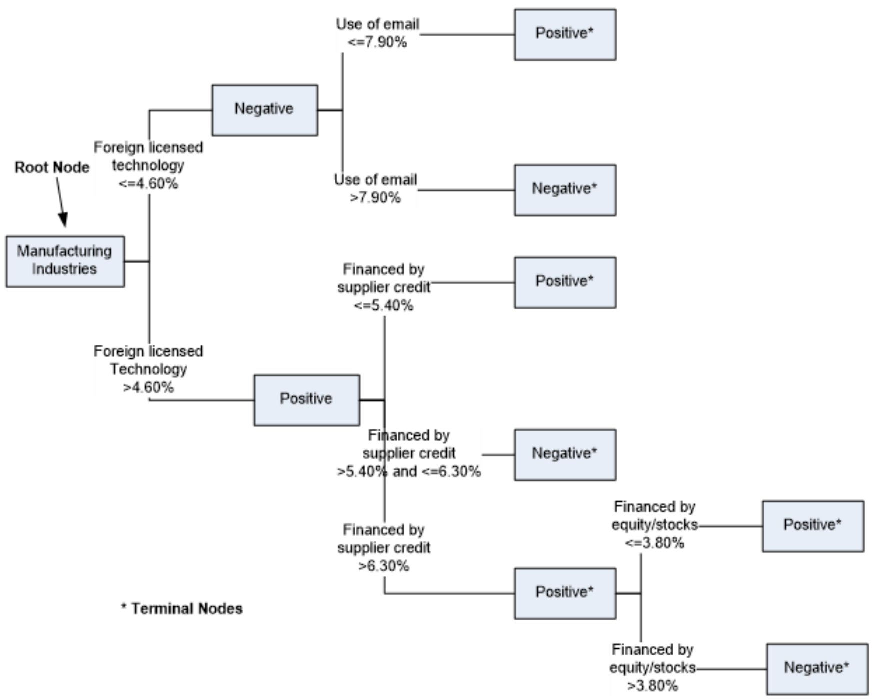


Figure 6. Decision tree for cluster 1



technological advancement improves sales growth, the subsequent split, based on email use, tells a different story. This cluster includes industries with lower technology advancement.

In the second branch, industries with more than 4.60% of firms using technology licensed from foreign companies, exhibit positive growth ($\chi^2 = 57.794$, $p<0.001$). This means technological advancement is a predictor of sales growth. Further down the branch, industries with less than or equal to 5.40% of working capital financed by supplier credit, exhibit positive growth. Those with more than 5.40% but less than or equal to 6.30% exhibit negative growth, and those with more than 6.30% exhibit positive growth ($\chi^2 = 20.598$, $p=0.046$). The last subset of industries, performance depends on the percent of investments financed by equity or stock sales. Those with less than 3.80%

of investments financed by equity or stock sales, exhibit positive growth, and those with more than 3.80% exhibit negative growth (χ^2 = 10.895, p=0.022). This cluster is the least technologically advanced, due to lower ICT predictors means used to define the clusters. The mean sales growth is negative, suggesting industries ought to develop technical competencies before relying heavily on finance. Using additional financing from equity or stock sales, while relying on supplier credit, implies too much reliance on financial institutions, causing negative sales growth.

Cluster 2

Cluster 2 DT accuracy is 87.88% and the tree (Figure 8) has three predictors, in descending importance (Figure 7). Unlike Cluster 1, geographical region and financial variables are important sales growth predictors. The top split – the value of collateral needed for a loan (expressed as a percentage of the loan amount) – has three branches, industries with an average collateral less than or equal to 170.80%, more than 170.80% but less than or equal to 207.30%, and those with more than 207.30%. The first branch has industries with an average collateral of 170.80%, generally exhibit positive growth ($\chi2$ = 59.354, p<0.001), and influenced by geographical region. This branch has industries in Africa and Central America exhibit negative growth, those in Eastern Europe, South America, and West Asia exhibit positive growth ($\chi2$ = 13.270, p=0.004). Industries in other regions did not fall into this cluster. Industries in Eastern Europe, South America, and West Asia, with less than 32.50% of their working capital financed by supplier credit, experience positive growth, and those with more than 32.50% exhibit negative growth ($\chi2$ = 16.782, p=0.001). High collateral strains a firm's finances and negatively influence performance (Yeo & Grant, 2019b). This branch confirms less reliance on supplier credit improves sales growth.

The second branch includes industries with an average collateral of more than 170.80% but less than or equal to 207.30%, exhibit negative growth (χ^2 = 59.354, p<0.001). The third branch has industries with average collateral of more than 207.30%, exhibit positive growth (χ^2 = 59.354, p<0.001). The third branch indicates high collateral leads to positive sales growth. Of the 12 industries in this branch, 2 exhibit negative growth and 10 exhibit positive growth, suggesting higher debt does not lead to negative sales growth for technologically advanced industries. High debt may be due to infrastructure investment to improve competitive advantage and sales growth.

Cluster 3

The DT accuracy is 87.67% and the tree (Figure 10) has two important predictors, none of which are ICT (Figure 9). In the top split, the proportion of investments financed by equity or stock sales, has three branches: industries with zero, more than zero but less than or equal to 10.00%, and industries

Figure 7. Predictor importance in cluster 2

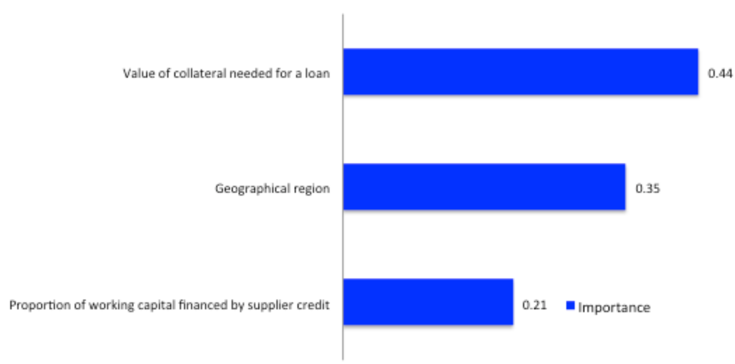


Figure 8. Decision tree for cluster 2

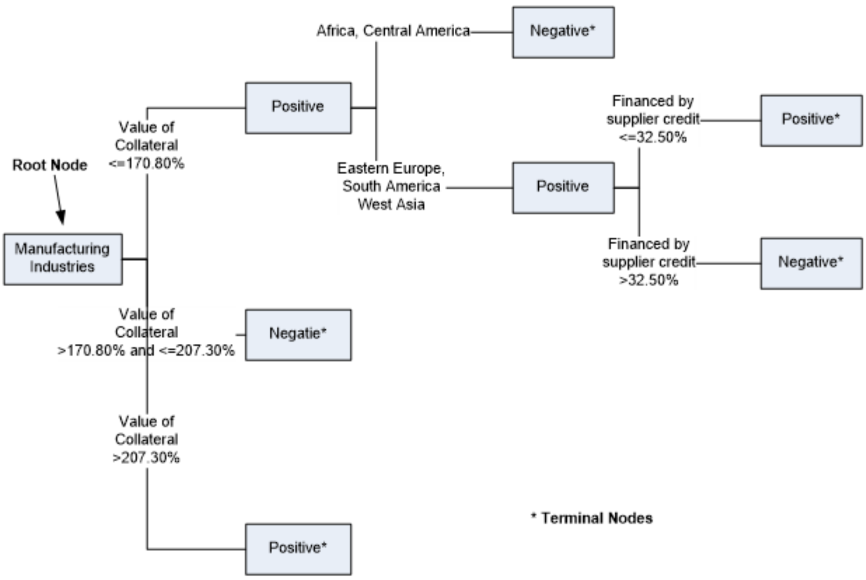
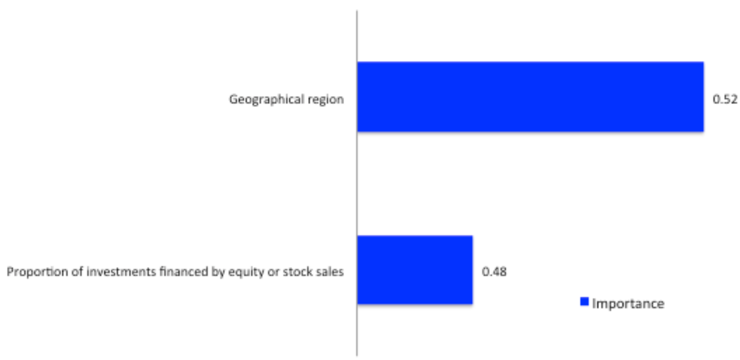


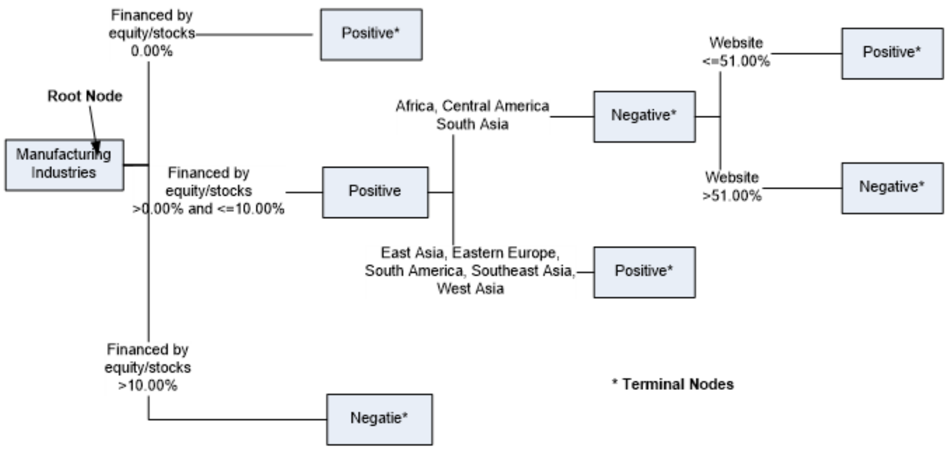
Figure 9. Predictor importance in cluster 3



with more than 10.00% of their investments financed by equity or stock sales. Industries in the first branch exhibit positive growth despite 12 of 15 having missing sales growth values, making interpretations difficult.

In the second branch, those with more than zero but less than or equal to 10.00%, and include geographical region, exhibit positive growth ($\chi^2 = 50.641$, $p<0.001$). Industries in Africa, Central America, and South Asia exhibit negative growth and those in East Asia, Eastern Europe, South America, Southeast Asia, West Asia, and Western Europe exhibit positive growth ($\chi^2 = 23.492$, $p=0.002$). Industries in Africa, Central America, and South Asia, with less than or equal to 51.00% of firms having their own website exhibit positive growth, and those with more than 51.00%, exhibit negative growth ($\chi2 = 11.374$, $p=0.020$). The appropriate use of websites, similar to email, is more important than simply using them. Some regions may be unable to fully leverage technology, causing negative growth. In the third branch, industries with more than 10.00% of their investments financed

Figure 10. Decision tree for cluster 3



by equity or stock sales, exhibit negative growth ($\chi2$ = 50.641, p<0.001). Of the seven industries, four exhibit negative growth, two exhibit positive growth, and one has missing data.

Cluster 4

The DT accuracy is 75.22% and significant predictors exclude ICT (Figure 12). The top split (Figure 11) is the proportion of investments financed by equity or stock sales. Disregarding those with missing sales growth values, most records in this cluster exhibit positive sales growth ($\chi2$ = 40.601, p<0.001). Those with average collateral less than 198.20%, exhibit positive growth (χ^2 = 12.206, p=0.042), depending on the proportion of working capital financed by supplier credit. Those with less than or equal to 6.60%, exhibit positive growth, those with more than 6.60% but less than or equal to 9.30% exhibit negative growth, and those with more than 9.30% exhibit positive growth (χ^2 = 18.839, p=0.009). Eight industries had 6.60% to 9.30% of working capital financed by supplier credit, of which five exhibit negative growth. These five may be anomalies, given that 45, the majority of the industries in this branch with average collateral of more than 198.20%, exhibit positive growth. Industries with average collateral exceeding

Figure 11. Predictor importance in cluster 4

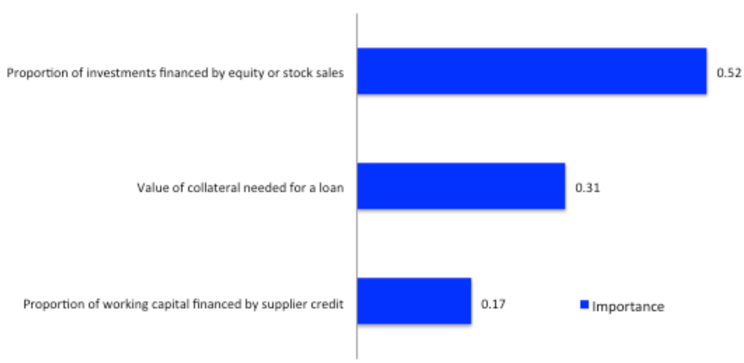
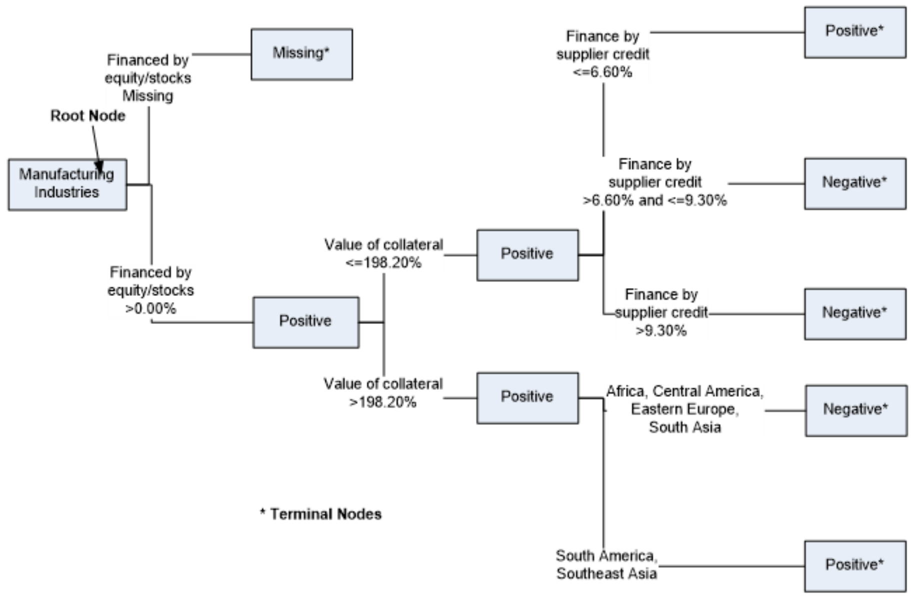


Figure 12. Decision tree for cluster 4



198.20% of loan value, exhibit positive growth (χ^2 = 40.601, p<0.001). This is influenced by geography as industries in Africa, Central America, Eastern Europe, and South Asia, exhibit negative growth, and those in South America and Southeast Asia exhibit positive growth (χ^2 = 14.730, p=0.020). The countries were absent from the cluster.

DISCUSSION AND CONCLUSION

Summary

Despite evidence of ICT economic impact (Chipidza & Leidner, 2019), ICT industry research is needed (Chae et al., 2018; Crowston & Myers, 2004) to improve inconsistent industry findings (Devaraj & Kohli, 2000; Schryen, 2013). ICT4D research requires contexts (Walsham, 2017), and Yeo and Grant (2019b) believe inconsistent ICT findings stem from their neglect, thus supporting our contextual approach. Karanasios (2014) suggests theories to unify and interpret ICT4D literature, but they are in short supply (Heffernan et al., 2016; Sein et al., 2019), supporting our use of IIF to frame our research model. Previous ICT4D studies use qualitative means (Lin et al., 2015) to bridge this methodological gap, hence data mining is used to overcome challenges of generating rigorous and testable hypotheses, creating new theory and knowledge to improve information systems research (Osei-Bryson & Ngwenyama, 2011). Our hybrid method of k-means clustering and CHAID DT to analyze how infrastructure, economy, geography influence industry sales, adds depth and rigor. Four distinct technologically advanced industry groups and different financial characteristics were identified. The predictive models in each group yielded high predictive accuracy. RQs are evaluated by the impact of the contextual variables on industry sales growth. Regarding RQ1, ICT are not major predictors of sales growth and important to the least technologically advanced industries. For RQ2, economic factors are the most consistent predictors across industry groups, and most important to clusters in the middle of the technologically advancement landscape. For RQ3, culture is important to the two most technologically advanced clusters.

Theoretical Perspectives of ICT in Context

Karanasios (2014) recommends using rigorous theories in ICT4D research, but contexts are often missing (Weisinger & Trauth, 2002), and ICT industry impact is unclear (Schryen, 2013). Contexts explain fragmented findings, so we advance ICT4D theories on how infrastructure, economy, and culture impact industry sales growth. The findings are used to abduct hypotheses for future theories (Osei-Bryson & Ngwenyama, 2011). The IIF posits culture, infrastructure, economy, and public policy are separate, inter-related constructs, and our findings suggest an embedded view. The clusters possess different technological advancement and financial maturity, and different performance predictors. Our proposed view is infrastructure should be embedded in the economy, and economy in culture. Our new theory is culture influences economic decisions, and economy and culture affect industry performance, which varies with technological advancement. For example, there is evidence that suggests culture drives tourism performance (Zhou & Sotiriadis, 2021). Figure 13 illustrates our proposed expansion of the IIF as a proposed theory for ICT4D. We posit infrastructure capabilities precede economy, illustrating technological infrastructure is embedded in economy. IIF is an explanatory theory for explaining empirical findings, using Gregor's (2006) typology of IS theories. We expanded its applicability by demonstrating its predictive capabilities. To test hypotheses on infrastructure, economy variables act as controls, and culture as controls for economy.

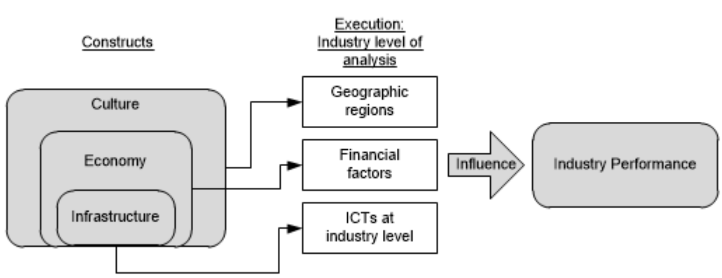
Figure 13 has theoretical and practical implications for country analysis to inform industry and public policies, and the interconnectedness of culture, economy, and infrastructure. This is particularly relevant to poor and developing countries and their rural communities (Appiah-Otoo & Song, 2021) that benefit most from ICT impact (Rumata & Sakinah, 2020). Xue, et al. (2008) demonstrate testable hypotheses from empirical findings serve as propositions to illustrate outcomes. Propositions fill a need for more analytical ICT4D research (Avgerou, 2017). Our first proposition informs IT-centric studies, information society, and both generate testable hypotheses. Public policy provides incentives, nurture new industries, protect mature ones, and elucidate the role of culture.

Proposition 1: Impact of ICT $= f$ (economy, culture, level of analysis)
Proposition 2: Impact of the economy $= f$ (culture, level of analysis)

Comparing the Industry Clusters

The DT accuracies are about 75% for the less technologically advanced clusters (1 and 4), and about 87% for the more advanced clusters (2 and 3). The four clusters have at least three important sales growth predictors, except Cluster 3 with two, and Cluster 1 with five. The predictor types differ by cluster. Considering the top two predictors in each cluster, Cluster 3 includes geographical region, and the proportion of investments financed by equity or stock. Region is a common predictor in Clusters 2 and 3, and so is, value of collaterals for a loan in Clusters 2 and 4, and investments by equity and stocks in Clusters 3 and 4. Top two predictors in Cluster 1 are percent of firms using technology licensed

Figure 13. A proposed theory for ICT4D



from foreign companies, and portion of working capital financed by supplier credit, respectively. The former is the infrastructure variable in the top two predictors across all clusters, appearing once. Economy variables dominate the top-two predictors, appearing five of eight times, once in Clusters 1, 2, and 3, and twice in Cluster 4. Next is region, appearing twice and once in Clusters 2 and 3 respectively, and infrastructure appearing once in Cluster 1.

Cluster 2 has industries with the highest percent of industries using email and websites, and the highest percent of industries with bank loans or lines of credit. The best predictor of industry performance in Cluster 2, is the value of collateral needed for a loan, and no infrastructure predictors appear in the top three. Aside from Cluster 2, Cluster 3 has the highest percent of firms using email and websites. Its best predictor is region, followed closely by the proportion of investments financed by equity or stock. Similar to Cluster 2, there are no important infrastructure predictors in Cluster 3. After Clusters 2 and 3, Cluster 4 has the next highest percent of industries using email and website. Its best predictor is the proportion of investments financed by equity or stock sales.

Our findings on RQ1 demonstrate infrastructure impact on industry sales growth is inconsistent, important to Cluster 1, and unimportant to others. The four clusters possess different technological advancement levels, based on the percent of industries using email and websites. There are differences among cluster predictors as Cluster 1 is the least technologically advanced and the only cluster where infrastructure is important. In response to RQ2, economy is most important across clusters and leads to Hypothesis One (H1): Financial factors are stronger predictors of manufacturing industry sales growth than ICT (infrastructure), stems from Proposition 1, and should be tested in future studies. H1 can inform public policy impact on sales growth when optimal infrastructure investment is determined.

The lack of ICT industry research (Crowston & Myers, 2004), and inconsistent results (Devaraj & Kohli, 2000; Schryen, 2013) were investigated by analyzing ICT impact on sales growth. RQ1 findings corroborate infrastructure impact is inconclusive (Orlitzky et al., 2003; Piget & Kossaï, 2013; Yeo & Grant, 2019b) and Yeo and Grant (2019b) suggest measuring ICT impact with contextual factors as different variables, may lead to inappropriate conclusions. Researchers should question how ICT impact performance, rather than if they do (Richardson & Zmud, 2002).

Clusters 3, 2, 4, and 1 are ranked in descending order of technological advancement. ICT are significant predictors in Cluster 1, with weaker sales growth, and not significant in the more advanced and better performing clusters. In Cluster 4, credit and loans are important, signifying the importance of economy, after acquiring infrastructure. Findings from RQ1 lead to Hypothesis Two (H2): Industries with a lower technological advancement experience stronger impact from ICT performance than those with higher technological advancement, and stems from Proposition 1. Testing H2 investigates whether technology capability threshold in an industry influence performance. Using benchmarking to identify industry capability threshold, contributes to practice.

Clusters 2 and 3, the most technologically advanced, have the highest percentages of industries possessing websites, using email, international quality certifications, and external auditors. Cluster 2 has the highest industry sales growth. The importance of geography to technologically advanced and financially matured industries (Clusters 2 and 3), provide answers to RQ3. It suggests culture influences industry sales growth when infrastructure capabilities and economy are in place. Because regions have different business practices, they influence industry performance, as in Clusters 2 and 3. This leads to H3a and H3b that stem from proposition 2; Hypothesis Three A (H3A): The impact of geography (culture) on industry performance varies with different levels of technological advancement (infrastructure). Hypothesis Three B (H3B): The impact of geography (culture) on industry performance varies with different levels of financial capabilities (economy). H3a and H3b contribute to theory on how culture influence industry practice and performance, as adapting to cultural informalities and crime in BRICS improves performance (Grant & Yeo, 2018a). Scholars and policy makers in ICT benefit from new theories on economy, public policy, and culture.

The Narrative of Infrastructure

Regarding RQ1, Cluster 1, the least technologically advanced, is the only cluster with average negative growth. ICT variables – the use of foreign-licensed technology and use of email – are the most important sales growth predictors, along with less important economy variables. It suggests infrastructure is necessary but insufficient and some level of infrastructure capability is required to improve sales. Next, an appropriate mix of infrastructure capability and economy is also required. These findings inform industry practice are validated by predictors in technologically advanced clusters with stronger sales. It is noteworthy that advanced clusters have no infrastructure predictors and are dominated by culture and economy. These lead to Hypothesis Four A (H4A): Infrastructure (ICT) and economy (financial factors) have a greater impact on sales growth than infrastructure alone, and Hypothesis Four B (H4B): Infrastructure (ICT) and economy (financial factors) have a greater impact on sales growth than economy alone. They stem from Proposition 1, and their theoretical contributions suggests future research to determine the mix of infrastructure and economy, for improving sales growth.

The findings suggest supplier credit, loan collaterals, and equity and stock are significant predictors in Cluster 1, but collectively are less important than infrastructure. The best predictors are economic, corroborating their importance for economic growth (King & Levine, 1993), and industry performance (Levine, 1997). Our findings suggest a required level of infrastructure is necessary to improve sales. In technologically advanced Clusters 2 and 3, culture impacts industry sales and corroborates the literature on geography (Piget & Kossaï, 2013), culture (Saxenian, 1996; Trauth, 2000; Weisinger & Trauth, 2002; Yeo & Trauth, 2009), and infrastructure (Liao et al., 2015; Torero & Von Braun, 2006).

Findings on RQ2 suggest access to finance improves industry performance but not for industries with insufficient infrastructure capabilities. Infrastructure does not guarantee strong performance, but is necessary for competitiveness (Koivunen et al., 2008). Websites and email use are helpful when used optimally (Baard & Nel, 2011) and insufficient infrastructure investment that causes poorly developed and maintained websites, impedes performance (Hahn, 2003; Hoffman, 2011). Website use is influenced by culture and underutilized in Eastern Europe due to users' distrust of ecommerce (Garnik, 2004). Knowing infrastructure spending and misusing technology may negatively impact performance, is important for IT strategy.

Applications to Policy Making

The impact of ICT informs theory and policy (Avgerou, 2010), but digital economies are not all alike as different countries and regions have different levels of technological advancement. The impact of ICT varies significantly with geography (Akpan, 2003). Culture, the best predictor in Cluster 3, is followed closely by investments financed by equity and stocks. In Cluster 2, geography being the second most important predictor, emphasizes cultural importance and its effect on economy and infrastructure. Both are more technologically advanced clusters, suggesting a basic ICT infrastructure must be present.

Culture influences economic growth and tourism (Zhou & Sotiriadis, 2021), shapes institutional behavior (Avgerou, Chrisanthi, 2003), and policies are more effective when tailored to local contexts (Rodrik, 2000; Yeo & Trauth, 2009). For example, Japan's economy, influenced by traditional values of cooperation, stability, and shared knowledge, is aligned with its policies and cultural context (Basu, 2003). At the same time, a strong financial industry drives IT innovation and economic growth (King & Levine, 1993; Levine, 1997). These point to the relevance of economic and cultural factors in ICT policies and initiatives. As a practical implication, policy makers can utilize local economic and cultural characteristics to inform ICT policy and initiatives.

Contributions and Limitations

The paper makes several contributions. First, it demonstrates how IIF, a qualitative model, can be used in empirical quantitative investigations. Second, a typical study uses a single method, but this hybrid method enriches the analysis. Third, answers to the three research questions on infrastructure, economy and culture, point to the importance of contexts in ICT4D research, adding to the existing body of knowledge. Fourth, it demonstrates how DT can be used for abductive reasoning to develop new propositions, hypotheses, and theories for future research. Fifth, the research findings have theoretical and practical implications for scholars and policy makers. Finally, we show how IIF, as an explanatory theory (Gregor, 2006), can be used as a predictive theory, and propose an expanded theory for ICT4D with embedded contexts.

The research has limitations. First, the number of predictors and industry records per country can be expanded, increasing scholarly and practical value. Second, adding cloud, enterprise, and other advanced technologies from developing countries (Heeks, 2020) can improve future infrastructure analysis. Websites and email are relevant to developing countries however, it is unclear if including advanced technologies make a difference. Third, expanding economy (such as output, wages, and employment) and public policy variables should benefit future research. Fourth, country-level findings suggest culture influence business practices due to unique cultural characteristics that can boost performance such as tourism (Zhou & Sotiriadis, 2021). Despite using country to represent culture (Hofstede, 1980; Palvia et al., 2017), better cultural measures can be considered. Finally, with more extensive data, cluster quality can be improved.

Nonetheless, we achieved our research objective of investigating infrastructure, economic, and cultural impact on industry sales growth, and using the results to abduct propositions (Xue et al., 2008) and explanatory hypotheses (Fann, 2012; Osei-Bryson & Ngwenyama, 2011) to develop ICT4D theory. We identified two propositions, four explanatory hypotheses, and a new theoretical framework (Figure 13).

CONFLICT OF INTEREST

The authors of this publication declare there is no conflict of interest.

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