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2007 Composite Learning Index: Robustness Issues and Critical Assessment

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Executive Summary

Lifelong learning is crucial to a country's continued competitiveness, prosperity and social cohesion. Be it for the complex nature of lifelong learning or lack of resources and enthusiasm, no country has had a means of gauging the extent of lifelong learning within its population. The Composite Leaning Index (CLI) developed by the Canadian Council on Learning shows how this gap might be filled (Canadian Council on Learning, 2007a). The CLI assesses the state of lifelong learning over time, for individual communities and across Canada using the conceptual four-pillar framework of lifelong learning proposed by UNESCO's International Commission on Education for the Twenty-first Century (Delors *et al.* 1996):

(a) *Learning to Know* (knowledge acquired in the classroom),

(b) *Learning to Do* (knowledge acquired at work),

(c) *Learning to Live Together* (knowledge acquired in the community),

(d) *Learning to Be* (knowledge acquired at home, or family).

The CLI reflects the relative extent to which a particular Canadian city or community possesses learning conditions that promote economic and social well-being. Made up of 17 indicators (24 metrics), the index takes into account factors as diverse as distance to learning institutions, services and resources, availability of workplace training, learning through sports and culture, volunteering and youth literacy to compile a profile of communities and, ultimately, the country.

This report aims at validating and critically assessing the methodological approach undertaken by the Canadian Council on Learning to build the Composite Learning Index. We briefly outline the definition and the framework for conceptualising lifelong learning, as these were chosen by Canadian Council on Learning for the development of the CLI. Our

focus is on the robustness assessment of the index, with a view to identify whether certain methodological choices distort the messages provided by the CLI.

The three key questions we raise are:

- *Is the Composite Learning Index internally sound and robust with respect to its applications?*
- *Does the CLI withstand validation through proxy measures of outcomes of learning?*
- *What scenarios could have been used to build the CLI and how do the results from these scenarios compare to the CLI?*

The robustness assessment of the CLI by means of multivariate analyses, dominance analysis and sensitivity analyses reveals no particular shortcomings in the index structure. In brief, the analyses demonstrates that the Composite Learning Index

a. is internally robust,
b. corrects for relationships between indicators (there is no double counting of information),
c. has no strong dominance of few indicators, but a rather balanced structure,
d. provides results that are not strongly affected by compensability issues among the underlying indicators,
e. can withstand external validation by proxy measures, such adult literacy and other economic and social benefits of learning,
f. is representative of a plurality of alternative methodological scenarios, and
g. is essentially a weighted average of seventeen indicators. This form is easy to communicate to the wider public. Yet, the statistical approach to estimate the weights may be harder to be understood by a non-statistically literate audience.

The CLI underwent this methodological revision *during* its construction a*nd at the end* of the process. By doing so, initially subjective design choices were corrected, modified, and ultimately justified, with a view to increase the reliability of the results. In this sense, the CLI development moved from a one-way design process to a circular approach. At first, an initial set of about 35 indicators underwent multivariate analysis to identify indicators that were highly correlated. This information was then fed back to either remove or sum up highly correlated indicators. In subsequent design steps (e.g. indicator grouping, aggregation or weighting), uncertainty and sensitivity analysis provided decision-support and guided the exploration and selection of various design options. This process was followed with a view to set the foundation for a balanced index from the start.

Data-driven narratives on lifelong learning issues in Canada are also discussed in this report with a view to show directions of discussions and messages that stem from an index-based analysis of lifelong learning. The aims of such as an index are, inter alia, to identify weaknesses, propose remedial actions, allow for easy spatial and temporal comparisons (benchmarking), to prioritize areas in Canada of relatively low lifelong content, monitor and evaluate policies effectiveness and ultimately to funnel resources to provinces through, for example, multilateral and bilateral agreements between Canadian cities.

The Composite Learning Index, being the first composite indicator to measure lifelong learning, should be considered as the starting point towards establishing an operational model of lifelong learning that could yield results for supporting the monitoring of this phenomenon. The considerations on the lifelong learning conditions captured and highlighted by the CLI could very much be the case for Europe, but they have, somehow to be measured first. The conceptual and methodological framework of the CLI bear the appealing and necessary features to render the Canadian Composite Learning Index a forerunner to a European counterpart.

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Acronyms

CCL	Canadian Council on Learning
CLI	Composite Leaning Index
DEA	Data Envelopment Analysis
ESWBI	Economic and Social Well-Being Index
EW	Equal weights
FA	Factor Analysis
OECD	Organisation for Economic Cooperation and Development
PCA	Principal component analysis
PISA	Programme for International Student Assessment
PSE	Post-secondary education
UNCTD	United Nations Conference on Trade and Development
UNDP	United Nations Development Programme
UNESCO	United Nations Educational, Scientific and Cultural Organization

1. The conceptual framework for measuring Lifelong Learning

Lifelong learning has an attitudinal nature and expresses the concept that "*It's never too soon or too late for learning*". It is a process that involves the development of knowledge, skills and values throughout all stages of a person's life—from early childhood through adulthood. Learning is not just an intellectual process, but one that involves all areas of life, including a person's role in the community, performance in the workplace, personal development and physical well-being. As a form of pedagogy, lifelong learning is often accomplished through distance learning or e-learning, continuing education, home schooling or correspondence courses. It also includes postgraduate programs for those who want to improve their qualification, bring their skills up to date or retrain for a new line of work. Internal corporate training has similar goals. The concept of lifelong learning is used by organisations to promote a more dynamic employee base, more qualified to react in an agile manner to a rapidly changing environment. In later life, especially in retirement, continued learning takes diverse forms, crossing traditional academic bounds and including recreational activities.

The main reason for societies' increasing interest on lifelong learning is the acceleration of scientific and technological progress. Despite the increased duration of primary, secondary and university education (14-18 years depending on the country), the knowledge and skills acquired during the childhood years are usually not sufficient for a professional career spanning four decades or more.

Be it for the complex nature of lifelong learning or lack of resources and enthusiasm, no country has attempted to provide an estimate of the lifelong learning conditions within its population. At the same time, in fields such as economy or environment, composite indicators of countries performance have been popular tools in presenting complex concepts by aggregating diverse sources of data to show trends over time, or versus other multidimensional phenomena. Yet, lifelong learning is of a rather particular nature: it is the product of many decisions, policies and individual choices, and cannot be addressed by a single ministry or jurisdiction. That is why an assessment of lifelong learning conditions would need to be done at a local rather than at a country level.

We would be in favour of a wide definition of lifelong learning that spans across different societies and contexts, as expressed by Aitcheson (2003, p.165): "*Lifelong education is a comprehensive and visionary concept which includes formal, non-formal and informal learning extended throughout the lifespan of an individual to attain the fullest* *possible development in personal, social and vocational and professional life. … A key purpose of lifelong learning is democratic citizenship, connecting individuals and groups to the structures of social, political and economic activity*".

The main question is how a concept such as lifelong learning can be measured. Countries around the world have identified lifelong learning as a strategic priority, but Canada is the first country to develop an index that assesses the state of lifelong learning over time, for individual communities and across the country. The Composite Learning Index (CLI) was first released in May 2006 by the Canadian Council on Learning (CCL). It was developed with a view to be useful and accessible to a wide audience, including policy-makers, education researchers and practitioners, individual students and parents.

The conceptualisation of the CLI (Cartwright *et al.* 2006) is based on the four-pillar framework proposed by UNESCO's International Commission on Education for the Twenty-first Century (Delors et al, 1996) and on studies carried out by agencies such as the OECD, and the goals of education as defined by ministries of education across Canada. The four pillars recognize the broad scope of lifelong learning—at home, in the classroom, at work and in the community and are:

(a) *Learning to Know* (knowledge acquired in the classroom, e.g. literacy, numeracy, critical thinking),

(b) *Learning to Do* (knowledge acquired at work, e.g. acquisition of applied skills that are often linked to occupational success, such as computer training, managerial training and apprenticeships),

(c) *Learning to Live Together* (knowledge acquired in the community, e.g. developing values of respect and concern for others, fostering social and interpersonal skills, and an appreciation of the diversity of individuals),

(d) *Learning to Be* (knowledge acquired at home, e.g. development of a person's body, mind and spirit; skills in this area include personal discovery and creativity, and can be acquired through reading, use of internet and activities such as sports and arts).

The CLI is made up of 17 indicators (built from 24 specific measures) of lifelong learning. These indicators, taken from reliable national surveys and other sound data sources, reflect a wide range of learning activities (Table 1). Box 1 to Box 4 (see Annex) provide detailed information on data sources and the reasoning behind the selection of each indicator. By drawing attention to the specific indicators and types of learning, the conceptual framework also provides an impetus to explore a variety of issues related to learning in Canada.

Table 1. Pillars and Indicators for conceptualising lifelong learning

Learning to Know (student skills, attendance in formal education, distance to learning institutions)	**Learning to Do** (job-related training, workplace training, distance to vocational training)	**Learning to Live Together** (citizen involvement & engagement, distance to community services)	**Learning to Be** (use of cultural resources, internet services, distance to cultural resources)
1. *Youth literacy skills (reading, math, problem solving)* (15-y old youth)	1. *Participation in job-related training* (% of 25-64y)	1. *Charitable giving* (% of households)	1. *Exposure to media* (% of households spending on internet and reading material)
2. *PSE Participation* (% of 20-24y)	2. *Availability of workplace training* (any type of classroom or workplace training)	2. *Volunteering* (% of Canadians engaged in unpaid activities as part of a group or organization)	2. *Learning through sports* (% of households spending on recreation and sports facilities)
3. *University attainment* (% 25-64y)	3. *Distance to vocational training* (average distance to the nearest vocational schools, business and secretarial schools)	3. *Participation in social clubs, organizat.* (% of households)	3. *Learning through culture* (% of households spending on admissions to museums, arts)
4. *High School Drop-out* (% 20-24y)		4. *Distance to Community institutions* (average distance to the nearest business, civic and social associations)	4. *Broadband internet access* (% of households with wireless, cable, and/or DSL services)
5. *Distance to learning institutions* (average distance to the nearest elementary and secondary schools, colleges and universities)			5. *Distance to cultural resources* (average distance to the nearest museums and art galleries)

Note: Table re-adjusted from information contained in "The 2007 Composite Learning Index" report.

Besides seeking the appropriate sources of data and indicators to fill in the four-pillar framework, great emphasis was given by the CCL-CLI team in identifying economic and social benefits of learning, such as income, employability, population health, civic engagement and literacy (Table 2). These outcomes are generally perceived as components of a society's well-being and were used as part of the statistical model to determine the strength of the relationship between the learning inputs and the social and economic outcomes. Four societal (adult literacy, population health, voters' participation, child development) and two economic (income, unemployment rate) outcomes of leaning were selected to accompany the lifelong learning framework.

Table 2. Social and economic outcomes of lifelong learning

Social Outcomes	*Economic Outcomes*
1. *Adult Literacy*	1. *Unemployment rate*
2. *Population health*	2. *Average household income*
3. *Voters' Participation*	
4. *Child development and school readiness*	

Note: Table re-adjusted from information contained in "The 2007 Composite Learning Index" report.

Adult literacy refers to a spectrum of skills—including reading and writing, document literacy, numeracy, and problem solving—that are critical for Canadians to succeed in life. Research has shown that adults with low levels of literacy have more difficulty in finding a job, and those who do find a job are much more likely to earn a lower wage and are less likely to receive employer-funded training to enhance their skills (CCL, 2007b). On the other hand, high levels of literacy are strongly correlated with high participation in community and social activities, greater civic engagement, and improved health. *Early childhood development* is defined as the first five years of a child's life and, as such, is a critical time for learning. The skills gained at this time set the stage for success throughout the rest of a person's life (Doherty, 1997). *Voter participation* provides a good indication for overall civic engagement. In order for democratic countries to function well, their citizens must be both informed and engaged (CCL, 2006). Improved *population health* is shown to be positively related to increased learning. Higher levels of education correspond to better general health and increased life expectancy (Wolfe and Haveman, 2001). This is because people with more education are less likely to drink heavily, smoke or live in polluted areas and are more inclined to exercise and eat better (Kenkel, 1991). OECD studies show that individuals with the skills and knowledge necessary to keep pace with labour-market requirements are less likely to be *unemployed* (OECD, 2005). *Income level*, or the earnings of individuals, could be seen as the "rate of return" on investments in learning. A recent study by the OECD shows that individuals who are better educated have greater opportunities to be employed and have better "rates of return" on investments in learning (OECD, 2001). Another international study indicates that one extra year of education is associated with, on average, 5% to 15% higher wages (Krueger and Lindahl, 1999).

2. Constructing the Composite Learning Index

Squeezing a complex system such as lifelong learning conditions into a single metric faces plenty of empirical challenges, e.g. data quality, indicator selection, indicators importance (Eakin and Luers, 2006). However, if done correctly, it may yield a powerful comparative assessment tool capable of capturing societal conditions that drive people's lifelong learning efforts. It can allow for comparisons across space and time by providing the technical opportunity to monitor change, identify problems, contribute to priority-setting and policy formulation (von Schirnding, 2002). Thus, an index in the context of lifelong learning can generate new information that would otherwise not be visible (Eyles and Furgal 2002).

The selection of an appropriate methodology is central to any exercise attempting to capture and summarize the interactions among the indicators included in an index. The literature review offered in the JRC/OECD (2005) Handbook on composite indicators discusses the plurality of the approaches that have been used in building a composite indicator and shows that some of the methodologies are suited (more or less) to the purposes for which they are employed. In particular, the authors stress the need for an explicit conceptual framework for the index, and the usefulness of multivariate analysis prior to the aggregation of the individual indicators. They review tools for imputation of missing information, methodologies for weighting and aggregation, and finally methods for assessing the robustness of the index using uncertainty and sensitivity analysis. In Table 3 we present a stylised 'checklist' to be followed in the construction of a composite indicator, which we have rearranged from the information contained in the Handbook. Of the steps involved in the development of a composite indicator we have, thusfar, touched upon the theoretical framework for measuring lifelong learning in Canada and the selected indicators to describe this phenomenon. In the coming sections we will discuss in detail the remaining steps, and present the conclusions of the analysis regarding methodological aspects, on one hand, and the messages (data-driven narratives) conveyed by the Canadian Composite Learning Index.

Table 3. Checklist for building a composite indicator

Step	*At the end of this Step the constructor should have…*
Theoretical framework provides the basis for the selection and combination of variables into a meaningful composite indicator under a fitness-for-purpose principle (involvement of experts and stakeholders is envisaged at this step)	• A clear understanding and definition of the multidimensional phenomenon to be measured. • A nested structure of the various sub-groups of the phenomenon (if needed). • A list of selection criteria for the underlying variables, e.g., input, output, process.
Data selection should be based on the analytical soundness, measurability, country coverage, and relevance of the indicators to the phenomenon being measured and relationship to each other. The use of proxy variables should be considered when data are scarce (involvement of experts and stakeholders is envisaged at this step)	• Checked the quality of the available indicators. • Discussed the strengths and weaknesses of each selected indicator. • Created a summary table on data characteristics, e.g., availability (across country, time), source, type (hard, soft or input, output, process)
Data treatment consists of - imputing missing data (e.g. single, multiple imputation); - examining whether there are outliers (as they may become unintended benchmarks; - taking logarithms of some indicators values, so that differences at the lower levels matter more; - transforming highly skewed data (e.g. square root, or logarithms).	• A complete data set without missing values • A measure of the reliability of each imputed value that allows assessing the impact of imputation on the composite indicator results. • Discussed the presence of outliers in the dataset • Made scale adjustments, if necessary. • Transformed the indicators, if necessary
Multivariate analysis should be used to study the overall structure of the dataset, assess its suitability, and guide subsequent methodological choices (e.g., weighting, aggregation)	• Checked the underlying structure of the data along the two main dimensions, namely individual indicators, countries (by means of suitable multivariate methods, e.g., PCA, FA, cluster analysis). • Identified groups of indicators or groups of countries that are statistically "similar" and provided an interpretation of the results. • Compared the statistically-driven structure of the data set to the theoretical framework and discussed eventual differences.

Normalisation should be carried out to render the variables comparable	• Selected a suitable normalisation procedure(s) with reference to the theoretical framework and the data properties.
Weighting and aggregation should be done along the lines of the underlying theoretical framework	• Selected the appropriate weighting and aggregation procedure(s) with reference to the theoretical framework. • Discussed whether compensability among indicators should be allowed.
Uncertainty and sensitivity analysis should be undertaken to assess the robustness of the composite indicator in terms of e.g., the mechanism for including or excluding an indicator, the normalisation scheme, the imputation of missing data, the choice of weights, or the aggregation method.	• Considered alternative methodological approaches to build the index, and if available, alternative conceptual scenarios. • Identified the sources of uncertainty in the development of the composite indicator and provided the composite scores and ranks with confidence intervals. • Conducted sensitivity analysis of the inference (assumptions), e.g. to show what sources of uncertainty are more influential in determining the scores/ranks.
Links to other indicators should be made to correlate the composite indicator (or its dimensions) with existing (simple or composite) indicators as well as to identify linkages through regressions.	• Correlated the composite indicator with relevant measurable phenomena, accounting for the variations of the composite indicator as determined through sensitivity analysis. • Develop data-driven narratives on the results. • Performed causality tests (if time series data are available).
Decomposition into the underlying indicators should be provided to reveal the main drivers for good/bad performance. Transparency is primordial to good analysis and policymaking.	• Profiled country performance at the indicator level to reveal what is driving the composite indicator results. • Performed causality tests (if time series data are available). • Performed path analysis to identify if the composite indicator results are overly dominated by a small number of indicators and to explain the relative importance of the sub-components of the composite indicator.
Visualisation of the results should receive proper attention, given that the visualisation can influence (or help to enhance) interpretability.	• Identified a coherent set of presentational tools for the targeted audience. • Selected the visualisation technique which communicates the most information. • Visualised the results of the composite indicator in a clear and accurate manner.

Note: rearranged (and extended) from the JRC/OECD (2005) Handbook on composite indicators

The methodological approach to build the CLI involved eleven steps and is summarized in Table 4. The indicators were first adjusted so that higher values correspond to higher levels of lifelong learning and then standardised (z-scores). Factor analysis was applied, within each pillar of learning, to extract the common factors, and also applied to extract a single common factor from the six outcomes of learning. Multiple regression analysis was next employed to estimate the weights to be attached to the extracted factors within each pillar, so that each pillar would bear the highest association to the single factor of outcomes. The pillar scores were calculated as the weighted average of the factor scores multiplied by the respective regression-derived weights. Pillar scores were next standardised. Principal components analysis was used to transform the four correlated pillars into four orthogonal (uncorrelated) pillars and multiple regression analysis was employed to estimate the weights to be attached to the four orthogonal pillars, so that the CLI would bear the highest association to the factor of outcomes. The CLI score was calculated as the weighted average of the four pillar scores multiplied by the respective regression-derived weights. Finally, the overall CLI scores were scaled for ease of communication and for comparison purposes with respect to the national CLI average.

The CLI methodology was entirely based on statistical analysis that aimed to bypass some of the arbitrary decisions on the weighting issue in particular. The CCL-CLI team refrained from an equal weighting scheme for the following reason: whilst there is a strong basis for the theoretical involvement of each indicator in lifelong learning, there is no reason to suggest that their roles are equal. Instead, it was decided that the weights to be attached to the indicators and pillars should be estimated by a combination of factor analysis and regression analysis. More specifically, factor analysis was applied to reduce, where possible, the set of observed (and correlated) indicators to a smaller number of unobserved (and uncorrelated) factors that have a common causation influence. Given the large number of Canadian communities used in the analysis ($n = 4576$), the correlations were not considered spurious. The unobserved factors take into account the correlation structure of the indicators set. The higher the correlation between the indicators, the fewer factors are needed to capture the relationships present in the dataset. Finally, the multivariate regression analysis (Step 5 and Step 9) provided the weights that maximise the association between the combined outcome of learning (ESWBI) and (a) each pillar of learning, and (b) the CLI.

Table 4. The Composite Learning Index Methodology

(1) Directional adjustment of indicators

Data were adjusted, so that higher values correspond to higher levels of lifelong learning. The (1-*value*) transformation was applied to the *distance*-related indicators, and to the *high school drop-out rate*.

(2) Standardisation of indicators

All indicators were transformed into z-scores by subtracting the sample mean and dividing by the sample standard deviation.

(3) Factor Analysis within each pillar of learning

Factor analysis was applied to extract orthogonal common factors with eigenvalues greater than 0.9, which explain at least 85% of the total variation contained in the indicators of a given pillar.

(4) Factor Analysis for the outcomes of learning

Factor analysis was applied to extract a single common factor from the six outcomes of learning (abbreviated as ESWBI- Economic and Social Well-Being Index).

(5) Regression Analysis for weight estimation

Multiple regression analysis was employed to estimate the weights to be attached to the extracted factors for each pillar, so that the pillar aggregate would bear the highest association to the ESWBI (dependant variable in the regression).

(6) Calculation of pillar scores

The pillar scores were calculated as the weighted average of the factor scores multiplied by the respective regression-derived weights.

(7) Standardisation of pillar scores

All pillar scores were transformed into z-scores by subtracting the mean and dividing by the standard deviation.

(8) Principal Components Analysis for the pillars

Principal components analysis was used to transform the four correlated pillars into four orthogonal (uncorrelated) pillars.

(9) Regression Analysis for weight estimation

Multiple regression analysis was employed to estimate the weights to be attached to the four orthogonal pillars, so that the CLI would bear the highest association to the ESWBI (dependant variable in the regression).

(10) Calculation of the CLI score

The CLI score was calculated as the weighted average of the four pillar scores (from Step 8) multiplied by the respective regression-derived weights (from Step 9).

(11) Final scaling of the CLI scores

The overall CLI scores were finally scaled for ease of communication and for comparison purposes with respect to the national CLI score.

3. Quantitative assessment of the Composite Learning Index

Despite the reasoning behind the steps in the CLI methodology, each of those steps can influence the CLI scores. We will assess the impact of the methodological choices made during the development of the CLI and compare the CLI results with other, more or less, sophisticated methodological scenarios in this and in the coming sections.

A clear understanding, at least in general lines, of the CLI methodology is crucial to the success of the robustness assessment of the index and it allows assessing the feasibility and reliability of the index. In other words, is it possible to reproduce the CLI results given the data and information provided to the public? The answer is "*Yes*". The CLI website provides enough information to the public, with some statistical knowledge, in order to replicate the entire CLI methodology and results.

Indisputably, the "CLI making" demands a sensitive balance between simplifying a social system and still providing sufficient detail to detect characteristic differences (Diener and Suh, 1997). This leaves scientists and policy makers with a complex measure that is almost impossible to verify, particularly since lifelong learning cannot be measured directly (Eyles and Furgal, 2002; von Schirnding 2002). It is therefore taken for granted that the CLI can not be verified. Yet, in order to enable informed policy making and be useful as policy and analytical assessment tool, the CLI needs to be assessed in regard to its validity and potential biases. The first question to be answered is:

- *Is the CLI internally sound and robust with respect to its applications?*

3.1. Relationship between CLI, indicators, pillars, and learning outcomes

Following the replication process, correlation analysis is performed to examine the relationship between the indicators, the pillars, the CLI and the learning outcomes. Correlation analysis is a basic but widely used tool for "confirming" the mathematical design of indices. Booysen (2002) recommends that a weak correlation between an underlying indicator and an index should result in the exclusion of the respective indicator from the process. A major drawback of correlation analysis though is the fact that a strong correlation does not necessarily imply a strong influence or representation of the indicator in the overall index. In other words, any random variable could potentially show strong correlation with the index without actually being part of the index. Yet, the higher the number of cases (e.g. communities) in the correlation analysis, the lower the probability that spurious correlations occur. To complement the correlation analysis, we perform sensitivity analysis (using regression coefficients) and further assess the impact on the CLI of excluding one indicator at a time.

A simple correlation between the CLI scores and the pillars scores reveals strong associations between them (Table 5). The CLI has very high correlation with the Learning to Be ($r = 0.93$) and the Learning to Do pillar ($r = 0.87$), and a fair relationship with the Learning to Live Together ($r = 0.61$) and the Learning to Know pillar ($r = 0.58$). Relationships among the pillars themselves vary. The most associated are the Learning to Do and Learning to Be pillar ($r = 0.68$). The least associated pillars are the Learning to Live together and the Learning to Know ($r = 0.15$). This result is desired, as it implies that the four pillars may account for different aspects of lifelong learning, yet partially overlapping and not entirely separable. All correlation coefficients are positive, showing performance in the same direction. At this point, we note that the correlations we study are carried out at the community level and therefore the relationships revealed should be considered at this resolution.

Table 5: Pearson's correlation coefficients for the CLI and its four pillars

	Learning To Know	Learning To Do	Learning To Live together	Learning To Be
CLI	0.58	0.87	0.61	0.93
Learning To Know		0.43	0.15	0.45
Learning To Do			0.64	0.68
Learning To Live together				0.43

All coefficients are significant ($p < 0.01, n = 4576$).

Correlation analysis between the CLI and its indicators reveals that all correlations are positive and significant at the 0.01 level. Only the correlation between the CLI and the *PSE Participation* appears random (Table 6). The CLI has fair correlation with two indicators in the Learning to Know dimension: *university attainment* ($r = 0.49$) and *high school drop-out* ($r = 0.55$). With indicators from the Learning the Do pillar, the CLI has high relationship to *participation in job-related training* ($r = 0.82$) and fair relationship to *availability of workplace training* ($r = 0.53$). In the Learning to Live Together pillar, only *volunteering* has a fair correlation ($r = 0.51$) to the CLI, the other correlations being much lower. Finally, in the Learning to Be pillar, the CLI has strong relationship with three indicators: *exposure to media* ($r = 0.85$), *learning through sports* ($r = 0.84$) and *learning through culture* ($r = 0.77$). The pair wise correlations among the indicators are relatively low, besides for two indicators in the Learning to Be pillar, *exposure to media* and *learning through sports* ($r = 0.76$).

Table 6: Pearson's correlation coefficients between the CLI and its indicators

Learning to Know		*Learning to Live Together*	
Youth literacy	**0.33**	Charitable giving	**0.20**
PSE participation	**0.04***	Volunteering	**0.51**
University attainment	**0.49**	Participation in social clubs and org.	**0.38**
Distance to learning institutions	**0.34**	Distance to community institutions	**0.26**
High school drop out rate	**0.55**		
Learning to Do		*Learning to Be*	
Job-related training	**0.82**	Exposure to media	**0.85**
Workplace training	**0.53**	Learning through sports	**0.84**
Distance to vocational training	**0.21**	Learning through culture	**0.77**
		Distance to cultural resources	**0.27**
		Broadband internet access	**0.21**

All coefficients are significant ($p < 0.01$, $n = 4576$); * coefficient non significant ($p >> 0.05$).

An additional point that we will anticipate here because it is related to the correlation issue, is the influence of the measurement error and sampling error on the statistically-derived weights for the different measures. The CLI indicators come from multiple sources: consequently, few indicators have large errors as a result of random error variance (fine geographic regions with small sample size), whilst others have large errors as a result of bias (large geographic regions with large samples whose statistics have been disaggregated to their constituent geographic regions). Some of the CLI indicators are very accurately measured (e.g., based on questions like, "Have you spent money on books or magazines in the past year?"), while others are based on fuzzy estimates (e.g., internet access is measured by penetration of broadband infrastructure). Due to the presence of these sources of error, the upper bound of several correlation estimates appears lower than it actually is. Thus, some indicators that may be very important in lifelong learning turn out to have lower weight attached to them because they have large sampling error and/or measurement error. Yet, the CLI methodology takes this error into consideration, although not explicitly stated (Cartwright, 2007).

3.2 Impact assessment of the indicators to the CLI results

Correlation analysis, though informative, is only indicative and does not suffice to quantify the impact of indicators within a composite indicator structure. Path Analysis (Wright, 1934; Pedhazur, 1982) can be applied to estimate the relative effect of the indicators on the overall composite indicator scores by taking into account (a) the correlation structure and (b) the standardized regression coefficients between the CLI scores (dependant variable) and the indicators values expressed as z-scores (independent variables). The total effect of an indicator I_i on the CLI will be the sum of the direct effect represented by the standardized regression coefficient relating the indicator I_i to the CLI and of the indirect effect of I_i through its correlation with the remaining indicators in the CLI dataset. Path analysis results could provide an estimate of the total effect of the indicators on the overall CLI scores but there are a number of assumptions that need to be made, among which: (i) the linearity of the relationship between variables; (ii) the absence of interaction effects between variables; (iii) the recursivity (all arrows flow one way with no feedback looping); and (iv) an adequate sample size.

These assumptions are satisfied in the CLI, since the CLI model is practically linear ($R^2 = 0.999$) and the only relatively high correlation between the CLI indicators is merely 0.76 ($r^2 = 0.58$), which is not high enough to indicate collinearity for the purposes of this analysis. Furthermore, there are 17 coefficients (= number of indicators) to estimate using more than 4500 cases (= number of communities), which satisfies the recommendation of 10 to 20 times as many cases as coefficients to estimate (Kline, 1998). Finally, we are assuming that the effect is only from the indicators towards the CLI and not the other way round (path analysis is used herein for confirmatory purposes and not to infer causality).

Path analysis results show that the CLI scores are not dominated by a small number of indicators (Table 7). In fact, more than half of the indicators have at least 5% effect to the CLI scores, and four of them exceed 10%. These four indicators are: *exposure to media* (11.2%), followed by *learning through sports* (11.0%), *job-related training* (10.9%), *learning through culture* (10.1%). More than 5% contribution comes from *youth literacy skills* (6.8%), *workplace training* (6.7%), *university attainment* (6.1%), *high school dropout* (5.8%) and finally *volunteering* (5.6%). Regarding the effect of the pillars to the CLI scores, the Learning to Be pillar has an average effect of 38.9% to the CLI scores. The Learning to Know pillar follows, with an effect of 24.6%. Finally, the Learning to Do and Learning to Live Together pillars have an effect of 21.0% and 15.5 %, respectively. Interestingly, the two pillars of Learning to Know and Learning to Do, which together represent the formal and non-formal types of learning, account for 45% of the lifelong learning scores in Canada. The informal learning, represented by the Learning to Live Together and Learning to Be pillars, accounts for 55% of the lifelong scores.

Table 7: Path Analysis results: effect of the indicators and pillars to the CLI scores

Learning to	Pillar	Indicator	Direct and indirect effect (%)	
	Know	Youth literacy skills	6.8	24.6
		PSE participation	1.3	
		University attainment	6.1	
		Distance to learning institutions	4.6	
		High school dropout	5.8	
	Do	Job-related training	10.9	21.0
		Workplace training	6.7	
		Distance to vocational training	3.5	
	Live Together	Charitable giving	2.1	15.5
		Volunteering	5.6	
		Participation in social clubs, organisations	3.9	
		Distance to Community Institutions	3.8	
	Be	Exposure to media	11.2	38.9
		Learning through sports	11.0	
		Learning through culture	10.1	
		Distance to cultural resources	4.1	
		Broadband internet access	2.5	

Although, the impact of the indicators (or pillars) to the CLI scores is not equal, and that would neither be expected nor desired, there is no particularly strong dominance of a small number of indicators on the CLI scores. This conclusion provides, in part, a further justification of the CLI methodology to be based on weights guided by statistical analysis and not by perception, or subjective choices. The use of statistically-driven weights in the CLI can serve a threefold purpose: (i) correlation and measurement error in the data are taken into account, (ii) the four pillars scores and the CLI scores bear the strongest possible association to the ESWBI scores, and (iii) there is no predominantly strong dominance of just few indicators on the CLI scores.

To complement and complete the analysis in this context, we calculate the impact of a single underlying indicator on the CLI results by excluding an indicator from the dataset and recalculating the CLI scores using the original methodology. The CLI results based on the full set of 17 indicators and on the reduced set of 16 indicators are compared. Comparison is made using the absolute differences between the percentile rank scores from both sets. A community with a percentile rank score of 75 performs better than 75% of the communities included in the dataset. Eliminating, one-at-a-time, eight indicators from the full dataset (listed below the *PSE participation* indicator in Table 8) would leave practically unaffected the ranking of the Canadian communities. The indicator *job-related training* (Learning to Do pillar) has the most notable impact: although half of the communities would not see a change of more than 4.1% in their percentile rank score, 5 out of 100 communities (95^{th} percentile column in Table 8) would shift by more than 18.4% positions. Besides some expected differences on the impact of the underlying indicators on the CLI, this analysis further confirms the previous conclusion that there is no strong dominance in the CLI.

Table 8: Impact on the CLI scores of the elimination of one indicator at-a-time

Pillar Learning to …	*Excluded indicator*	*Absolute differences of the percentile rank scores between the CLI and the (17-1) reduced set of indicators over the 4576 communities in Canada*		
		Median	*95th percentile*	*Max*
DO	Job-related training	4.1	18.4	33.4
KNOW	University attainment	1.8	6.2	17.6
BE	Learning through culture	1.8	8.4	12.7
KNOW	High school drop-out rate	1.4	5.4	8.6
DO	Distance to vocational training	1.4	5.1	14.2
BE	Learning through sports	1.3	7.0	13.7
BE	Exposure to media	1.2	6.0	10.4
LIVE Together	Volunteering	1.1	3.4	11.3
KNOW	PSE participation	1.0	3.6	7.7
KNOW	Youth literacy skills	0.9	3.2	6.0
LIVE Together	Participation in social clubs, org.	0.9	3.1	7.0
LIVE Together	Charitable giving	0.8	2.9	6.6
LIVE Together	Distance to Community Institut.	0.8	2.9	5.9
BE	Distance to cultural resources	0.8	3.5	7.4
BE	Broadband internet access	0.2	0.8	1.6
KNOW	Distance to learning institutions	0.1	0.5	1.2
DO	Workplace training	0.1	0.5	1.3

Parsimony principles would suggest to exclude those indicators from the CLI framework that do not have an important impact on the CLI results (Gall, 2007). This, however, may not be advisable, unless excluding certain indicators is supported by expert opinion on the relevance of the indicators to the issue. An eventual revision of the framework in a few years time may be undertaken, when available time series will allow a thorough study of the causal links between the lifelong learning indicators selected and the social and economic outcomes of learning.

4. Cluster analysis and Factor analysis as diagnostic tools

4.1 Cluster analysis: setting short-term targets

Several Canadian regions may have similar CLI scores but very different patterns across the seventeen indicators or pillars of learning. To help local authorities identify peer regions that are similarly situated with respect to the individual indicators, we applied cluster analysis (Kaufman and Rousseeuw, 1990). A brief description of cluster analysis and its role during the CLI assessment is provided in Box 8 (Annex). Cluster analysis was carried out at the metropolitan area level ($n = 142$) instead of the community level ($n = 4576$) that is generally used throughout this report, because the number of communities would have been extremely high for this type of analysis.

Based on the information provided by the seventeen indicators of learning, the 142 metropolitan areas in Canada have been grouped statistically into clusters in a way that the degree of association between two metropolitan areas is maximal if they belong to the same cluster and minimal otherwise. Consequently, the members of each cluster are more similar to each other than to members of other clusters. Going over the mere identification of clusters, our aim is to provide cluster-specific targets for the indicators of learning, which could be reached in the short-term by the metropolitan areas, before such areas would engage themselves in efforts to reach longer term targets.

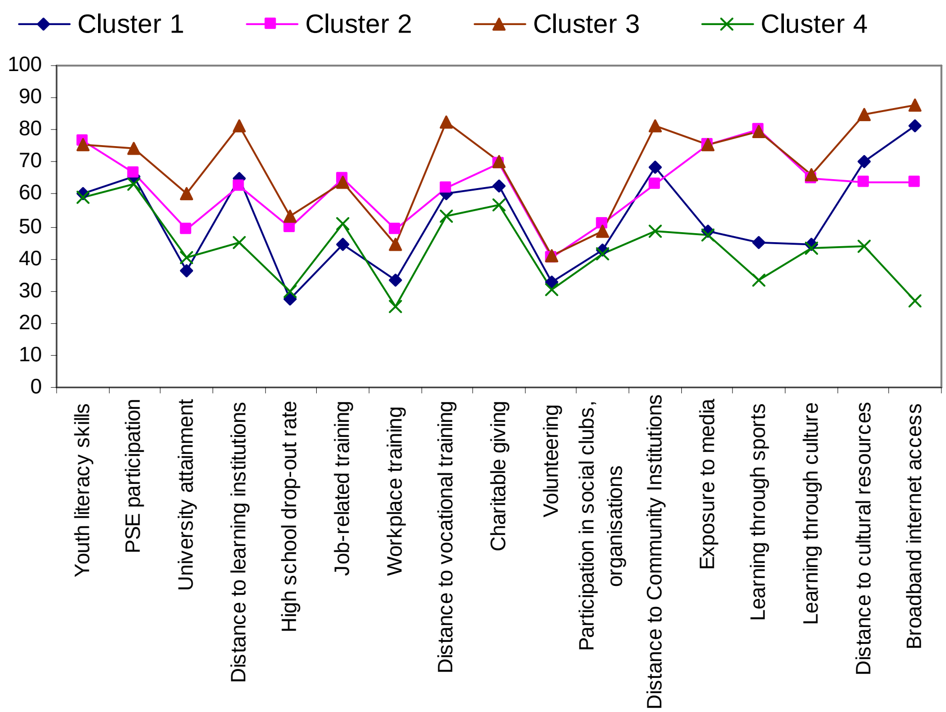
We used hierarchical clustering (ward's method) of the metropolitan areas across the 17 indicators to identify the number of clusters. We then used k-means clustering to allocate the metropolitan areas in these clusters. This process generated four clusters (Table 9) that can help local authorities look beyond geographic peer groups or other type of classification in order to identify models of lifelong learning success from areas facing similar challenges.

Cluster One groups 60 metropolitan areas from all the Canadian provinces besides British Colombia. The metropolitan areas included in this group have moderate to low performance in most indicators of learning (Figure 1). They perform well in three indicators: *distance to community institutions, distance to cultural institutions* and *broadband internet access*. **Cluster Two** includes 36 metropolitan areas from Prince Edward Island, Ontario, Saskatchewan, Alberta and British Colombia. They have good to high performance in indicators of learning, such as *youth literacy* (OECD-PISA study), *exposure to media*, *learning though sports* and *learning through culture*. Their only challenges are concentrated on two indicators, the *distance to cultural resources* and *broadband internet access*. The 36 metropolitan areas in **Cluster 3** belong to Quebec, Ontario, Saskatchewan, Alberta and British Colombia. They have the highest performance in all indicators of learning. **Cluster Four** contains only 10 metropolitan areas from New Brunswick, Quebec, Ontario and Alberta. They are characterized by relatively poor performance in the *university attainment*, *workplace training, distance to community institutions, learning through sports, distance to cultural resources* and *broadband internet access*.

Table 9. Clusters of metropolitan areas (alphabetical order) based on the 17 indicators

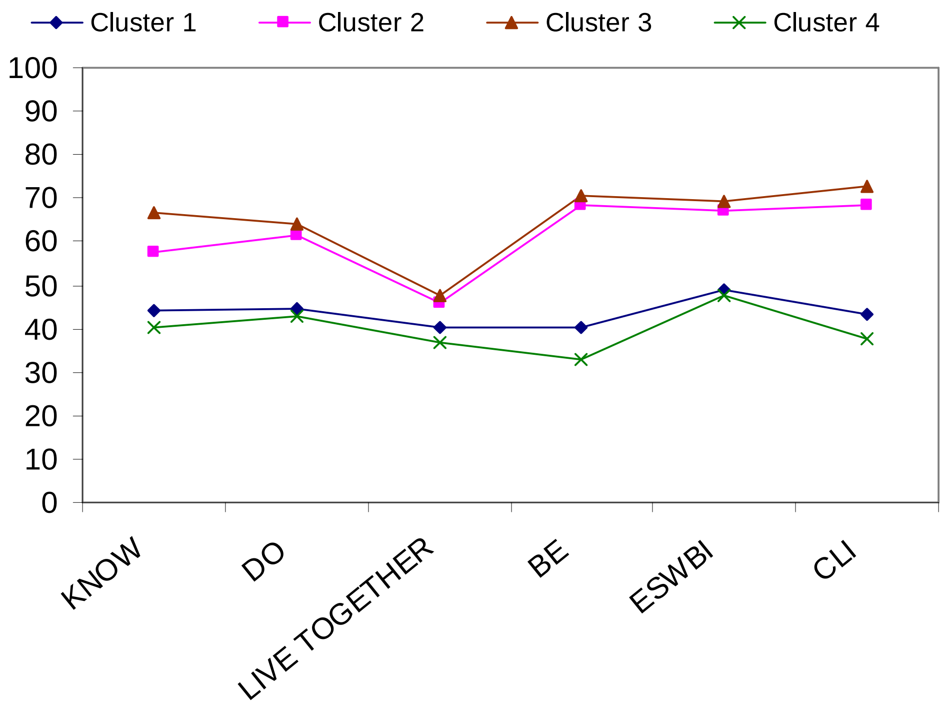
Cluster 1 (60 cases)		Cluster 2 (36 cases)		Cluster 3 (36 cases)		Cluster 4 (10 cases)
Alma	Prince A	Barrie	Orillia	Abbotsfo	Midland	Amos
Bathurst	Québec	Brantfor	Owen	Bellevil	Okotoks	Baie-Com
Bay Robe	Rimouski	Calgary	Sou	Brockvil	Oshawa	Brooks
Brandon	Rivière-	Campbel1	Penticto	Camrose	Ottawa -	Edmundst
Campbell	Rouyn-No	Canmore	Petawawa	Cobourg	Parksvil	Frederic
Cape Bre	Saguenay	Centre W	Peterbor	Collingw	Pembroke	La Tuque
Charlott	Saint-Ge	Chilliwa	Port Alb	Cornwall	Red Deer	Lethbrid
Chatham-	Saint-Hy	Cold Lak	Port Hop	Courtena	Salmon A	Miramich
Corner B	Saint-Je	Edmonton	Powell R	Cranbroo	Squamish	Saint Jo
Cowansvi	Salaberr	Grande P	Prince G	Dawson C	St. Cath	Thunder
Dolbeau-	Sarnia	Halifax	Prince R	Duncan	Stratfor	
Drummond	Sault St	Kamloops	Quesnel	Estevan	Tillsonb	
Elliot L	Sept-Île	Kawartha	Regina	Fort St.	Toronto	
Granby	Shawinig	Kelowna	Saskatoo	Guelph	Vancouve	
Grand Fa	Sherbroo	Kenora	Terrace	Hamilton	Victori1	
Greater	Sorel-Tr	Kingston	Vernon	Hawkesbu	Wetaskiw	
Joliette	St. John	London	Williams	Ingersol	Woodstoc	
Kentvill	Summersi	Nanaimo	Wood	Kitchene		
Lachute	Swift Cu	Norfolk	Buf	Kitimat		
Leamingt	Temiskam					
Lloydmin	Thetford					
Matane	Thompson					
Medicine	Timmins					
Moncton	Trois-Ri					
Montréal	Truro					
Moose Ja	Val-d'Or					
New Glas	Victoria					
North B1	Windsor					
North Ba	Winnipeg					
Portage	Yorkton					

Figure 1. Cluster means across the 17 indicators of lifelong learning



We next calculated the average score per pillar of learning, the average ESWBI score and the average CLI score across the members of each cluster (Figure 2). The metropolitan areas in Cluster 3 appear to have, on average, the highest scores in the four pillars of learning, the ESWBI, and in the CLI. The metropolitan areas in Cluster 2 follow, with average scores slightly lower than those in Cluster 3. Lower scores, on average, are achieved by the metropolitan areas in Cluster 1, followed by the metropolitan areas in Cluster 4. An interesting feature of Figure 2 is the clear splitting of the average scores per cluster group of the Canadian metropolitan areas across the pillars of learning, the CLI and the ESWBI, whilst this type of (aggregated) information did not enter the cluster analysis. Recall that cluster analysis was carried out based on the 17 indicators of learning, without any further assumption on the pillar structure, weighting or aggregation method.

Figure 2. Average values per cluster group: pillars, CLI, ESWBI



The results of cluster analysis show that the 17 selected indicators are able to distinguish between the lifelong learning conditions of the Canadian metropolitan areas and that the CLI reflects, without distorting, the information content in the dataset. It can be further concluded that given the lifelong learning diversities of the metropolitan areas in Canada, it is unlikely that all metropolitan areas can reach some long-term targets for the indicators of learning, equal, for example, to the maximum value in the dataset. To this end, we would suggest to use the clustering of the metropolitan areas, so as to set short-term targets for immediate pursue by the metropolitan areas (Table 10). Just to give an example, metropolitan areas that belong to Cluster 1 should first attempt to reach a *university attainment* at 26.7% within their adult population aged 25-64, which is equal to the short-term target and it would be easier to reach, prior to focusing efforts on the harder to reach long-term target at 37.7%.

Table 10. Short-term and long-term targets for the indicators of learning

	Short-term targets for each cluster group of Canadian metropolitan areas (max value in the cluster)				Long-term targets (max value in the dataset)
	Cluster 1 $n = 60$	Cluster 2 $n = 36$	Cluster 3 $n = 36$	Cluster 4 $n = 10$	Entire dataset $n = 142$
Learning to Know					
Youth literacy skills (PISA score)	546.0	546.0	546.0	546.0	546.0
PSE participation (%)	47.0	47.5	48.2	47.5	48.2
University attainment (%)	26.7	34.1	37.7	26.3	37.7
Distance to learning inst.(km)	9.6	9.8	8.7	9.6	9.8
High school drop-out rate (%)	7.4	7.4	3.8	7.7	3.8
Learning to Do					
Job-related training (%)	30.0	31.0	33.4	30.0	33.4
Workplace training (%)	64.0	77.4	64.0	60.3	77.4
Distance to vocational training (km)	8.3	8.6	7.9	9.1	7.9
Learning to Live Together					
Charitable giving (%)	91.5	87.3	87.3	76.9	91.5
Volunteering (%)	62.4	62.3	89.7	57.1	89.7
Participation in social clubs, etc (%)	30.6	24.8	24.8	20.2	30.6
Distance to Community Inst. (km)	9.1	10.5	8.5	10.0	10.5
Learning to Be					
Exposure to media (%)	73.5	81.3	81.3	70.8	81.3
Learning through sports (%)	48.4	59.5	59.5	40.2	59.5
Learning through culture (%)	41.0	51.6	51.6	44.0	51.6
Distance to cultural resources (km)	7.5	7.6	7.2	8.7	7.2
Broadband internet access (%)	1.0	1.0	1.0	0.6	1.0

4.2 Factor Analysis: identifying the statistical dimensions of the dataset

The 17 selected indicators of the CLI framework were allocated into the four pillars of learning based on expert consultation and according to the following conceptual grouping: Learning to Know (knowledge acquired in the classroom), Learning to Do (knowledge acquired at work), Learning to Live together (knowledge acquired in the community), Learning to Be (knowledge acquired at home). In this section, we follow an alternative approach to group the indicators. We employ factor analysis and let the data decide on which dimension to be included based on the correlation structure of the data. A brief description of factor analysis and its role during the CLI assessment is provided in . The results show that, if we force a structure of four dimensions, the four retained factors (upon varimax rotation) account for 68% of the variance of the entire dataset (Table 11). The statistical grouping of indicators into the four factors is somehow different from the conceptual one. For example, all four *distance*-related indicators would be grouped together under factor 2, unlike the original version of the CLI, in which each pillar of learning includes the relevant distance-related measure. However, it seems hard, and beyond the conceptual one, the interpretation of the four factors.

Table 11. Squared factor loadings of the 17 CLI indicators

		Factor 1	Factor 2	Factor 3	Factor 4
Learning to Know	Youth literacy skills	0.25	0.01	0.52	0.03
	PSE participation	0.00	0.01	0.02	0.74
	University attainment	0.22	0.01	0.01	0.53
	Distance to learning institutions	0.01	0.70	0.01	0.00
	High school drop-out rate	0.16	0.05	0.30	0.05
Learning to Do	Job-related training	0.68	0.00	0.03	0.02
	Workplace training	0.21	0.00	0.30	0.14
	Distance to vocational training	0.00	0.33	0.03	0.17
Learning to Live together	Charitable giving	0.01	0.01	0.47	0.01
	Volunteering	0.14	0.00	0.64	0.06
	Participation in social clubs, organis.	0.09	0.00	0.29	0.06
	Distance to Community Institutions	0.00	0.74	0.03	0.00
Learning to Be	Exposure to media	0.71	0.00	0.06	0.00
	Learning through sports	0.69	0.01	0.05	0.02
	Learning through culture	0.67	0.00	0.00	0.04
	Distance to cultural resources	0.00	0.66	0.00	0.00
	Broadband internet access	0.00	0.59	0.01	0.00
	Eigenvalue	3.85	3.12	2.77	1.88
	Explained variance	23%	18%	16%	11%

Important squared loadings (>0.30) are highlighted in grey

A further piece of information that can be provided by factor analysis is that the current set of 17 indicators contains slightly more statistical dimensions than the four included in the conceptual framework. Based on the most common rule-of-thumb, the Kaiser criterion[1], there are five statistical dimensions in the dataset, which account for 74.4% of the variance of the original set. According to a more conservative rule, the Joliffe criterion[2], the number of statistical dimensions in the dataset is slightly higher (six statistical dimensions). These results show that the indicators included in the CLI express diverse aspects of lifelong learning and support their inclusion in the lifelong learning framework.

[1] Kaiser criterion: keep factors with eigenvalues above 1.0. The simplest justification to this rule is that it doesn't make sense to add a factor that explains less variance than is contained in one individual indicator.

[2] Joliffe criterion: keep factors with eigenvalues above 0.70. This rule may result in twice as many factors as the Kaiser criterion, and it is less often used.

Table 12. Eigenvalues of the factors based on the lifelong learning indicators

Factor	Eigenvalue	Explained variance (%)	Explained variance cumulatively (%)
1	4.63	27.2	27.2
2	3.54	20.8	48.1
3	2.14	12.6	60.7
4	1.32	7.7	68.4
5	1.01	5.9	74.4
6	0.73	4.3	78.6
7	0.62	3.6	82.3
8	0.51	3.0	85.3
9	0.46	2.7	88.0
10	0.43	2.5	90.5
11	0.37	2.2	92.6
12	0.32	1.9	94.5
13	0.26	1.5	96.0
14	0.22	1.3	97.3
15	0.20	1.2	98.5
16	0.15	0.9	99.3
17	0.11	0.7	100.0

Note: Extraction method: Principal Components Analysis, n=4576.

5. Comparative assessment of scenarios to build the CLI

There is evident creativity in the community of composite indicators developers, which not only comes as a response to the demands of the user/stakeholder community, but it also reflects the disagreements within the research community on which indicators influence a particular phenomenon and on their relative importance (Cutter *et al.*, 2003). When building an index to capture lifelong learning conditions, it is therefore necessary to take stock of existing methodologies to avoid eventual skewness in the assessment and decision-making.

By acknowledging a variety of methodological assumptions in the development of an index that are intrinsic to policy research, one can determine whether the main results change substantially when the assumptions are varied over a reasonable range of possibilities (Saisana *et al.*, 2005; Saisana and Tarantola, 2002; Saltelli *et al.*, 2000). The advantages offered by considering different scenarios to build the CLI could be: to gauge the robustness of the CLI results, to increase its transparency, to identify the Canadian communities whose performance improves or deteriorates under certain assumptions, and to help frame the debate around the use of the lifelong learning index for policy making. The alternative scenarios to build the CLI should, however, bear certain quality features:

1. No strong dominance of few indicators at the expense of others in the index.
2. High association between the index scores and the ESWBI.
3. No deliberate bias of the index results against few Canadian communities.
4. Simplicity and ease at reproducing the index.

There are two main questions to be addressed next.

- *Does the CLI withstand external validation through proxy measures?*
- *What scenarios could have been used to build the CLI and how do the results from these scenarios compare to the CLI?*

5.1 Description of the Scenarios

We identified 25 alternative and diverse scenarios, all with their advantages and implications, to build an alternative version of the lifelong learning index for Canada, using as basis for the development of the scenarios various examples of composite indicators (for a review see Bandura, 2005; JRC/OECD, 2005; Saisana and Tarantola, 2002). These scenarios account, some more than others, for the quality features we raised above. The scenarios differ in four main aspects: four-pillar structure (preserved or not), normalisation method (z-scores[3] or Min-max[4] approach), weighting method (different statistical methods to derive the weights or equal weighting) and aggregation method (linear, geometric or multi-criteria analysis) (Table 13).

Scenario 1 resembles the CLI methodology, but it differs in that the weights to be assigned to the factor scores within each pillar and across pillars do not derive from regression analysis versus the ESWBI scores. The weights are, instead, estimated as equal to the proportion of the variance explained by a factor, as done for example in the Trade and Development Index (UNCTD, 2005) or in the Summary Indicators of Product Market Regulation (Nicoletti *et al.*, 2000). **Scenario 2** differs from S1 in that, instead of z-scores, a Min-max approach is used.

In **Scenarios 3 and 4**, we abandon the four-pillar structure and let all indicators interact to finally arrive at a single index using Factor Analysis. The two scenarios differ in the normalisation method.

In **Scenarios 5 and 6**, Factor Analysis is used within each dimension, but all four dimensions are subsequently averaged to produce the overall score. Again, the two scenarios differ in the normalisation method.

The classical equal weighting approach in building an index is represented by **Scenarios 7 and 8**, which differ in the normalisation method only. All indicators are simply averaged without considering the four-pillar structure.

In **Scenarios 9 and 10**, we average the indicators within each dimension, and subsequently average the four dimensions. The two scenarios differ in the normalisation method only.

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[3] Standardisation (or Z-scores): Each normalised indicator value is equal to the raw value minus the average across communities and divided by the standard deviation, so that all normalised indicators have similar dispersion across communities. This approach converts all indicators to a common scale with an average of zero and standard deviation of one, yet the actual minima and maxima of the standardized values across communities vary among the indicators. We standardized, so that each indicator has a mean of 50 and a standard deviation of 10, to allow the use of geometric aggregation which requires strictly positive values.

[4] Min-max scaling: Each normalized indicator value is equal to the raw value minus the minimum value across communities and divided by the range of values. In this way, the normalized indicators have values within [0, 1]. This approach increases the impact of indicators with small range of values to the overall composite indicator, but it preserves the information on the different variances between indicators. Both these features, depending on the case, could be a desirable or an undesirable property. In our case, the range of values for the indicators was set to [10, 100], to allow the use of geometric aggregation which requires strictly positive values.

Table 13: Methodological scenarios for the development of the CLI

Scenario	Pillar Structure	Normalisation	Weighting	Aggregation
CLI	Preserved	z-scores	FA within pillar, Regression weights to Factors, FA pillars, Regression weights to pillars	Linear
S1	Preserved	z-scores	FA within pillar, FA pillars	Linear
S2	Preserved	Min-max	FA within pillar, FA pillars	Linear
S3	Not preserved	z-scores	FA all indicators	Linear
S4	Not preserved	Min-max	FA all indicators	Linear
S5	Preserved	z-scores	FA within pillar, EW pillars	Linear
S6	Preserved	Min-max	FA within pillar, EW pillars	Linear
S7	Not preserved	z-scores	EW all indicators	Linear
S8	Not preserved	Min-max	EW all indicators	Linear
S9	Preserved	z-scores	EW within pillar, EW pillars	Linear
S10	Preserved	Min-max	EW within pillar, EW pillars	Linear
S11	Preserved	z-scores	FA within pillar, FA pillars	Geometric
S12	Preserved	Min-max	FA within pillar, FA pillars	Geometric
S13	Not preserved	z-scores	FA all indicators	Geometric
S14	Not preserved	Min-max	FA all indicators	Geometric
S15	Preserved	z-scores	FA within pillar, EW pillars	Geometric
S16	Preserved	Min-max	FA within pillar, EW pillars	Geometric
S17	Not preserved	z-scores	EW all indicators	Geometric
S18	Not preserved	Min-max	EW all indicators	Geometric
S19	Preserved	z-scores	EW within pillar, EW pillars	Geometric
S20	Preserved	Min-max	EW within pillar, EW pillars	Geometric
S21	Preserved	Raw data	FA within pillar, FA pillars	Multi-criteria
S22	Not preserved	Raw data	FA all indicators	Multi-criteria
S23	Preserved	Raw data	FA within pillar, EW pillars	Multi-criteria
S24	Not preserved	Raw data	EW all indicators	Multi-criteria
S25	Preserved	Raw data	EW within pillar, EW pillars	Multi-criteria

(EW: Equal weights; FA: Factor Analysis)

In **Scenarios 11 to 20**, we employ geometric aggregation, in which the indicators values are raised in a power equal to the weight and subsequently multiplied together into an index. Structure, normalisation and weighting vary as in Scenarios 1-10 where linear aggregation was used.

Finally, in **Scenarios 21 to 25** we use multi-criteria analysis to aggregate the information. A brief description of the multi-criteria analysis is provided in Box 9.. Structure and weighting issues vary as previously. Multi-criteria analysis uses ordinal, as opposed to cardinal, information on the indicators values, thus there is no need to normalise the indicators and the raw data are used instead.

5.2 Comparative assessment of the methodological scenarios

The first objective in comparing the alternative scenarios to build the index is linked to "*validating the immeasurable*" or to provide an answer to the question:

- *Does the CLI withstand external validation through proxy measures?*

To this end, we evaluate the CLI ability, and that of the alternative scenarios, to represent the actual problem at hand, i.e. is the model described by the CLI or by the scenarios a legitimate model of lifelong learning? Some modelers argue that it is impossible to validate and/or verify models of non-closed systems (Oreskes *et al.*, 1994). This is ultimately true. In the context of this report, however, the goal is not to establish the absolute truth or verify the CLI but rather to test whether analytical procedures provide enough empirical evidence to reject the CLI.

Due to lack of a direct outcome of lifelong learning, the CCL-CLI team resorted to calibrating the CLI versus proxy measures, such as adult literacy, early childhood development, voter participation, population health, unemployment rate and income, that are considered in the relevant literature as important outcomes of learning (Table 2).

Research in Canada on the *adult literacy* has shown that: (i) adults with low literacy levels have more difficulty finding a job, (ii) those with low literacy levels who do find a job are much more likely to earn a lower wage and are less likely to receive employer-funded training to enhance their skills, (iii) high levels of literacy are strongly correlated with high participation in community and social activities, greater civic engagement, and improved health (Canadian Council on Learning, 2006)

Doherty (1999) shows that *early childhood development* in terms of school readiness can predict the likelihood that the child will develop a strong sense of self-respect and concern for others, strong literacy, numeracy and problem-solving skills, and an interest in lifelong learning.

Voter participation provides an indication of the proportion of adults who demonstrate a basic level of political knowledge and engagement. A detailed discussion of the relationship between voter turnout, civic engagement and learning in (Canadian Council on Learning, 2006).

Positively related are increased learning and improved *population health*. Higher levels of education correspond to better general health and increased life expectancy (Wolfe and Haveman, 2001). This is because people with more education are less likely to drink heavily, smoke or live in polluted areas and are more inclined to exercise and eat better (Kenkel, 1991). A detailed discussion on the effects of literacy on health in Canada is offered in (Canadian Council on Learning, 2006).

The direction of causality between determinants and outcomes of lifelong learning triggers additional discussions (Adda *et al.*, 2003; Moffitt, 2005). Some researchers may tend to see the *income* level as a driving force of lifelong learning. Others could see a high income as the reward of a high level of lifelong learning (OECD, 2001). An international study (Krueger and Lindahl, 1999) reports that one extra year of education is associated with, on average, 5% to 15% higher wages. Regarding the economic benefits of lifelong learning, a recent OECD report shows that individuals with the skills and knowledge necessary to keep pace with labour-market requirements are less likely to be *unemployed* (OECD, 2005).

Without trying to resolve the conceptual debate on the direction of the cause-effect between determinants and outcomes of learning, we would expect that the selected CLI indicators influence social and economic outcome gradients and that they possess sufficient explanatory power to account for the economic and social differences between and within communities in Canada.

Correlation analysis reveals a strong association between the aggregate of the outcomes of learning- the ESWBI and either (a) the CLI scores, or (b) the scenarios scores (Table 14). Compared to any of the scenarios, the CLI has the highest correlation to the ESWBI (r =0.84). The alternative scenarios correlate fairly (e.g. Scenario 4, r = 0.55) to relatively high (e.g. Scenario 2, 12, 21, r =0.79) with the ESWBI. *Adult literacy*, the most apparent outcome of learning, could further serve our analysis for the external validation of the CLI and its alternatives. The CLI has the highest correlation to *adult literacy* (r =0.75) compared to the other scenarios (r = 0.38 for Scenario 4 to r = 0.69 for Scenario 21). The *population health* is only modestly correlated with either scenario (r = 0.24 to 0.28) or the CLI. *Voters' participation* and *early childhood development* bear even weaker associations to the CLI scores or the scenarios. The relationships between the CLI or the scenarios and the two economic outcomes of learning, *unemployment rate* and *income*, are good and close to those of the *adult literacy* (r = 0.44 to 0.74). These results show that the methodological choices in combining the selected set of 17 indicators into an index may increase or decrease the degree of association between the composite indicator of lifelong learning and the ESWBI. The choices made to build the CLI, however, have lead to an index that is mostly related to the aggregate of the economic and social outcomes of learning and to adult literacy, two proxies indicators/indices of lifelong learning.

One final comment is in place on the reasons behind extracting a single common factor to represent the six outcomes of learning (see Box 7 for more details). Factor analysis shows that the six outcomes of learning have three common factors with eigenvalues greater than 1.0 and an explanatory power of almost 80% of the variance in the outcomes dataset. However, the CCL-CLI team decided to extract a single common factor, as only the first factor was deemed to represent lifelong learning, whilst the remaining factors were considered to be linked to more income-related issues. This explains why outcomes of learning such as *population health*, *voters' participation* and *early childhood development* bear relatively low association to the composite lifelong scores.

Table 14. Correlation between the scenarios and economic/social outcomes of learning

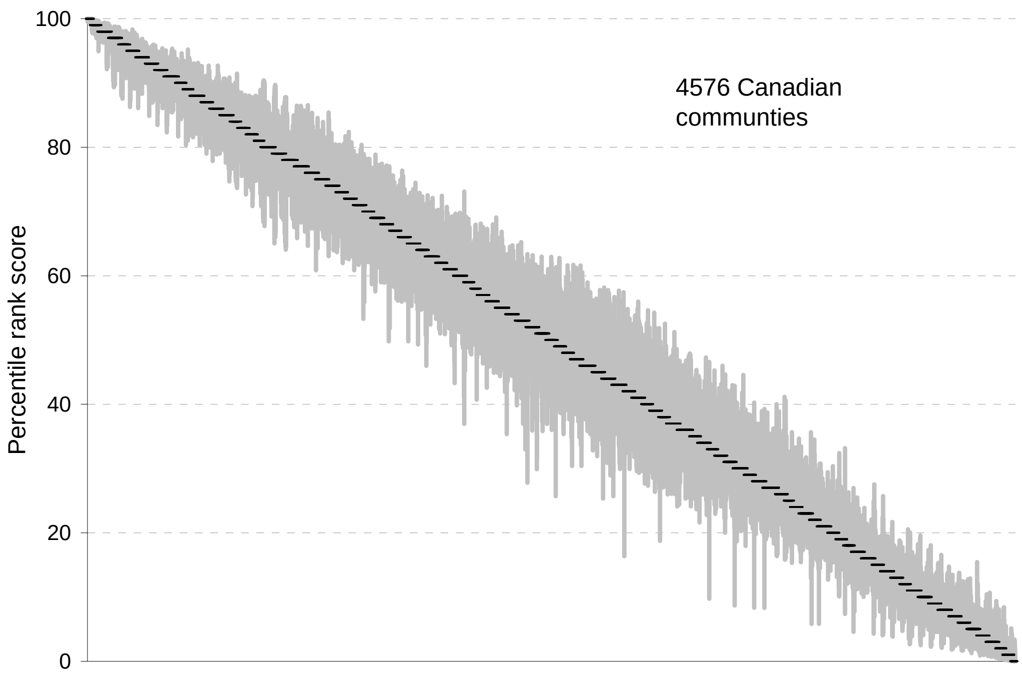
	Economic and Social Well-Being Index	*Adult Literacy*	*Population health*	*Voters' Participation*	*Child Development*	*Unemployment rate*	*Income*
CLI	0.84	0.75	0.24	0.27	0.17	0.68	0.71
Scenario 1	0.78	0.65	0.26	0.09	0.20	0.66	0.74
Scenario 2	0.79	0.65	0.26	0.11	0.20	0.66	0.74
Scenario 3	0.59	0.45	0.24	0.15	0.11	0.47	0.59
Scenario 4	0.55	0.38	0.25	0.14	0.10	0.44	0.58
Scenario 5	0.75	0.64	0.25	0.13	0.17	0.62	0.69
Scenario 6	0.76	0.63	0.26	0.13	0.18	0.63	0.71
Scenario 7	0.70	0.57	0.27	0.23	0.12	0.53	0.66
Scenario 8	0.66	0.50	0.28	0.22	0.11	0.50	0.65
Scenario 9	0.72	0.61	0.27	0.23	0.13	0.55	0.65
Scenario 10	0.68	0.55	0.28	0.23	0.12	0.51	0.65
Scenario 11	0.77	0.63	0.26	0.08	0.20	0.65	0.74
Scenario 12	0.79	0.66	0.26	0.12	0.20	0.67	0.74
Scenario 13	0.58	0.43	0.25	0.14	0.11	0.47	0.59
Scenario 14	0.61	0.44	0.25	0.16	0.12	0.50	0.62
Scenario 15	0.74	0.62	0.25	0.12	0.17	0.61	0.70
Scenario 16	0.77	0.65	0.26	0.14	0.18	0.64	0.71
Scenario 17	0.69	0.55	0.27	0.22	0.12	0.53	0.66
Scenario 18	0.69	0.53	0.26	0.25	0.12	0.53	0.66
Scenario 19	0.71	0.60	0.27	0.23	0.13	0.55	0.66
Scenario 20	0.71	0.56	0.27	0.26	0.12	0.54	0.66
Scenario 21	0.79	0.69	0.27	0.13	0.20	0.66	0.72
Scenario 22	0.60	0.46	0.25	0.19	0.11	0.48	0.59
Scenario 23	0.77	0.68	0.26	0.15	0.18	0.63	0.69
Scenario 24	0.72	0.60	0.27	0.27	0.12	0.55	0.66
Scenario 25	0.74	0.64	0.27	0.26	0.13	0.57	0.65

We next come to answer the third question:

- *[…] and how do the results from these scenarios compare to the CLI?*

The point behind this question is to reveal whether any deliberate bias against some communities in Canada is introduced by making certain methodological choices in building the CLI. In Figure 3 we summarize the results from the 25 methodological scenarios and present the median and the best and worst scores over the 25 scenarios, after eliminating the minimum and maximum scores to avoid eventually skewed results from a given scenario. This graph aims at answering arguments, well pointed out by Andrews et al. (2004: 1323), that many indices “rarely have adequate scientific foundations to support precise rankings: […] typical practice is to acknowledge uncertainty in the text of the report and then to present a table with unambiguous rankings”.

Figure 3. Median and associated best and worst scores over 25 scenarios



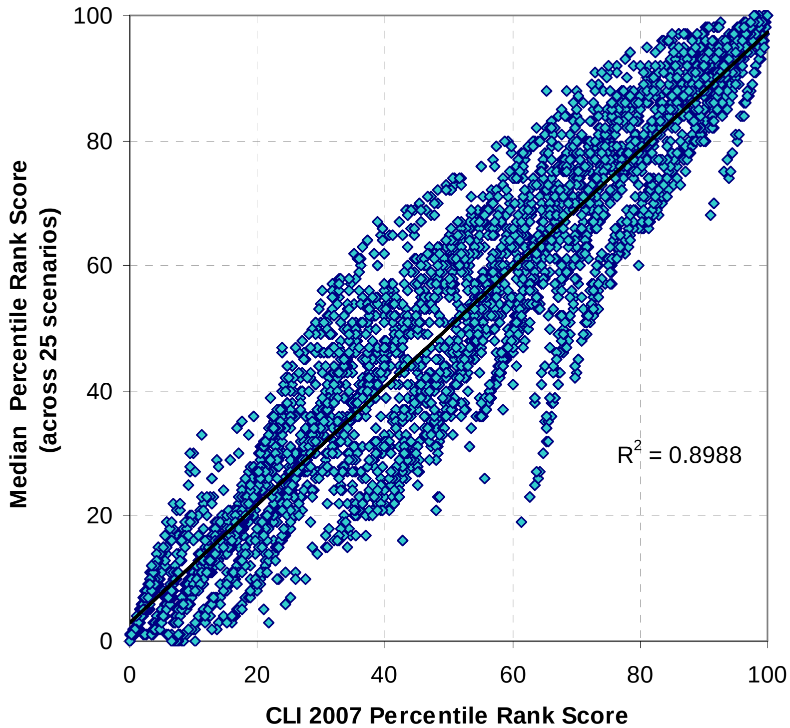
The results in Figure 3 express percentile rank scores (recall that a percentile score of 75 implies that 75% of the communities are below that level). There is no particularly volatile section in the graph and almost all Canadian communities see few positions of change, depending on the scenario. However, there are very few communities, dispersed at various levels of lifelong learning, that see more than 25% of the communities performing better or worse than them, depending on the scenario. These are five communities that belong to Newfoundland & Labrador province (Gander, Grand Falls-Windsor, Clarenville, Lewisporte, Labrador City), one community from the Manitoba province (Altona), two communities from Saskatchewan (Eyebrow, Cochin), nine communities from the Alberta province (Improvement District No. 24, Kinuso, Opportunity No. 17, Nampa, Hines Creek, Rainbow Lake, McLennan, Donnelly, Birch Hills County) and one community from British Columbia (Northern Rockies B) (see list in Table 15). Any messages conveyed by the lifelong learning index for those eighteen communities should, thereafter, be formulated with great caution and be considered as only indicative or suggestive.

Table 15. Canadian communities with highly volatile scores in lifelong learning

Altona	Improvement District No. 24
Birch Hills County	Kinuso
Clarenville	Labrador City
Cochin	Lewisporte
Donnelly	McLennan
Eyebrow	Nampa
Gander	Northern Rockies B
Grand Falls-Windsor	Opportunity No. 17
Hines Creek	Rainbow Lake

Although certain methodological scenarios would favour some communities more than others, the median score across the 25 scenarios could be seen as an unbiased "summary picture" of the lifelong learning conditions in Canada. The correlation between the CLI (percentile rank scores) and the median is very high (R^2=0.899, p<0.001, n=4576, see Figure 5). This result shows that the CLI provides an unbiased summary picture of the lifelong learning conditions in Canada. Therefore, the CLI, besides bearing the strongest associations to important outcomes of learning (such as adult literacy) and to the ESWBI, it is also representative of a plurality of methodological scenarios.

Figure 4. Association between the CLI and the median across 25 scenarios



Caution, however, is required when discussing the CLI scores for several communities, for which the CLI percentile rank score deviates significantly from the median percentile rank score. Unfortunately, there is no pre-established threshold for such a comparison that would allow to identify for which communities the scores may not be reliable. For the purposes of our analysis, we consider that more than 25 points difference between the CLI percentile rank score and the median score may help spot out the communities whose CLI score is highly sensitive to the methodological choice made during the development of the index. A "25 points threshold" indicates that more than 25% (one-forth) of the communities in Canada could potentially perform better or worse than any the communities listed in Table 16 (in alphabetical order), depending on whether the CLI or the median across the 25 scenarios is considered as a better description of the lifelong learning conditions in Canada. Every statement on the lifelong learning conditions , estimated by the CLI scores, for those communities (about 150 out of 4576) should thereafter, be made with caution, indicating that the results are merely 'indicative' or 'suggestive'. For the remaining communities, the CLI scores can reliably be used for policy-making or for benchmarking purposes.

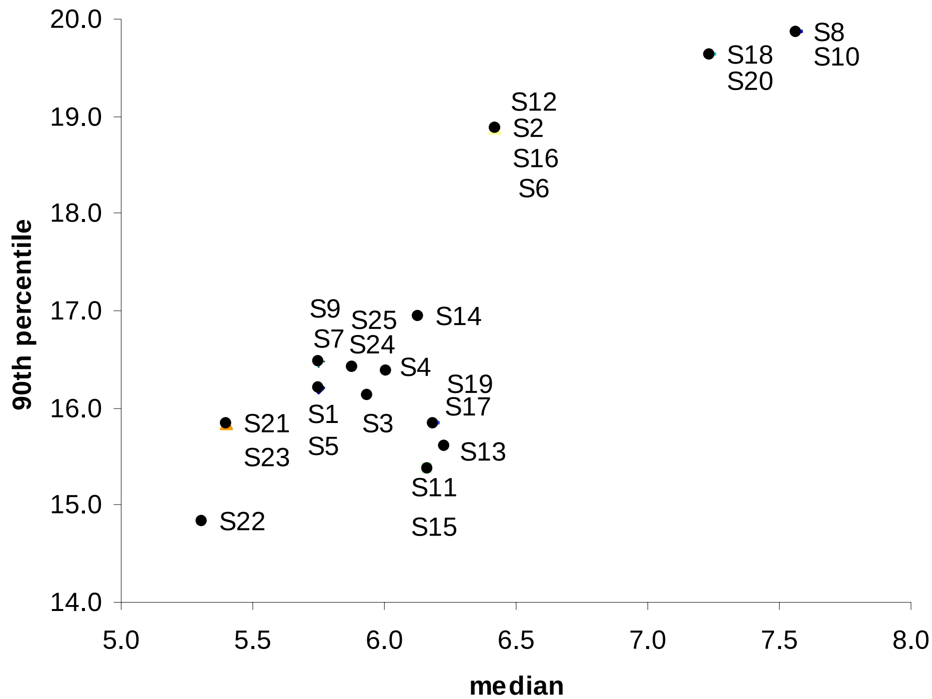
Table 16. Communities whose CLI scores should be treated with caution

Abernethy	Delburne	Key West No. 70	Roche Percee
Abernethy No. 186	Derwent	Kisbey	Rochon Sands
Alix	Disley	Kneehill County	Scott No. 98
Argentia Beach	Drummond	Lacombe County	Seba Beach
Baie Verte	Eckville	Lakeland County	Shippagan
Bas-Caraquet	Edmundston	Lamèque	Silver Beach
Bathurst	Elmsthorpe No. 100	Le Goulet	Smoky Lake County
Belle Plaine	Elnora	Leduc County	Souris Valley No. 7
Bengough No. 40	Empress	Lewisporte	Special Area No. 2
Benson No. 35	Enniskillen No. 3	Lomond	Special Area No. 3
Bentley	Florenceville	Lomond No. 37	Special Area No. 4
Beresford	Forget	Mackenzie No. 23	St. Leonard
Betula Beach	Gander	Macoun	St. Paul County No. 19
Big Lakes	Ghost Lake	McTaggart	Sunbreaker Cove
Birchcliff	Gladmar	Minton	Sundance Beach
Bittern Lake	Glen Ewen	Miramichi	Sylvan Lake
Blackfalds	Glendon	Montmartre No. 126	Tecumseh No. 65
Bonnyville No. 87	Golden Days	Moose Creek No. 33	The Gap No. 39
Botwood	Golden West No. 95	Moose Mountain No. 63	Tracadie-Sheila
Bowden	Goodwater	Mount Pleasant No. 2	Tribune
Brazeau County	Grand Falls / Grand-Sault	Mountain View County	Tullymet No. 216
Bristol	Grand Falls-Windsor	Myrnam	Twillingate
Brock No. 64	Grandview	New Norway	Two Hills County No. 21
Browning No. 34	Griffin No. 66	Norglenwold	Vulcan County
Bruderheim	Gull Lake	Norris Beach	Wainwright No. 61
Campbellton	Halbrite	North Grove	Waiparous
Caraquet	Half Moon Bay	Northern Sunrise County	Walpole No. 92
Carmangay	Happy Valley No. 10	Ogema	Warburg
Centreville	Heward	Opportunity No. 17	Wawken No. 93
Ceylon	Horseshoe Bay	Osage	Wellington No. 97
Chamberlain	Improvement District No. 12	Paintearth County No. 18	Wetaskiwin County No. 10
Chauvin	Improvement District No. 13	Parkland Beach	White Sands
Clarenville	Improvement District No. 24	Petit Rocher	Willingdon
Clear Hills No. 21	Improvement District No. 25	Ponoka	Wood Buffalo
Clive	Innisfail	Ponoka County	Woodstock
Coalfields No. 4	Itaska Beach	Poplar Bay	Yellow Grass
Creelman	Jarvis Bay	Provost No. 52	Yellowhead County
Crystal Springs	Kananaskis	Reciprocity No. 32	Youngstown
Cymri No. 36	Kendal	Red Deer County	
Dalhousie	Kenosee Lake	Rimbey	

Complementary to this analysis, we study the impact of the 25 scenarios on the lifelong learning (percentile rank) scores, compared to the CLI results. To this end, the percentile rank score is calculated for each community and each scenario and the absolute difference between that score and the CLI percentile rank score is calculated. The median and the 90th percentile of those absolute differences over the entire set of the Canadian communities is computed.

Figure 5 presents the results. The more distant from the origin a methodological scenario is, the more it influences the results. Scenario 8 and 10, both of linear-type aggregation and with a min-max normalisation of the indicators, but with either equally weighting the indicators within each pillar (Scenario 10) or equally weighting the indicators without considering a pillar structure (Scenario 8), produce percentile rank scores that deviate more than 7.6 points (max 100) for half of the communities, or more than 19.7 points (max 100) for 10% of the communities. Slightly lower is the impact on the results of Scenario 16 or Scenario 18. These scenarios differ from Scenario 8 and 10 on the use of geometric aggregation, instead of a linear aggregation.

Figure 5. Sensitivity analysis: impact of each of the 25 scenarios to the CLI



Note: median versus 90th percentile (over 4576 communities) of the absolute differences in the percentile rank score between a given scenario (S1, …, S25) and the CLI

When using equal weighting and either linear or geometric aggregation, as in the case of the scenarios 8, 10, 16, 18, then issues of compensability (high values in some indicators offset very low values in other indicators) and double counting of information due to correlated indicators) may distort the results. Regarding the compensability issue, a solution to mediate this is to use a non-compensatory multi-criteria analysis or at least a multi-criteria approach based on ordinal information on the indicators. The five scenarios in which multi-criteria analysis is employed (Scenario 21 to 25) provide results that are relatively similar to the CLI ($r_S \approx 0.95$). This conclusion goes in favour of the CLI, which, despite its linear form, the results it provides are not subject to compensability issues. Furthermore, the double counting of information has been dealt with in the CLI methodology by using statistically-based weights by means of factor analysis and multivariate regression analysis. Additionally, the CLI is essentially a weighted average of 17 indicators. This simple form is easy to communicate to the wider public, although the statistical approach to estimate the weights may be harder to be understood by a non-statistically literate audience.

5.3 Data envelopment analysis: a tool to estimate region-specific weights

Several policy issues on lifelong learning in Canada entail an intricate balancing act between supra-national concerns and the region-specific policy priorities. If one opts to compare the multi-dimensional performance of the Canadian regions by subjecting them to a fixed set of weights, this may prevent acceptance of the index on grounds that a given weighting scheme might not be fair to a particular region. This issue has already been dealt with in Chapter 5, where the CLI methodology was compared with the results from different scenarios and it was shown that the CLI does not provide a biased picture of the lifelong learning status in Canada as the CLI results are very similar to those produced when using the median of the different scenarios. Another approach could have been to use Data Envelopment Analysis (DEA), a statistical approach that yields most favourable, region-specific weights, as opposed to using a single set of weights used for all regions. A brief description of this method and how it was applied to the CLI data is given in Box 10. These DEA-derived weights are endogenously selected, so as to maximise the index score for each region given the indicators' values for the other regions.

When applying the DEA method, it is essential to place reasonable bounds on the weights; otherwise a region in Canada could achieve a perfect index score simply by assigning zero weight to those indicators for which its performance is very low. To preclude this possibility, we attached upper and lower bounds on the shares, i.e. on the proportion of each indicator over the index score. The relative lower and upper bounds for the 17 indicators in the CLI framework are determined based on the number of indicators contained in each pillar. If equal weighting was applied to the indicators per pillar, then each indicator in the Learning to Know pillar would receive a weight equal to 0.05 (=1/5/4). Similarly, the weights for the indicators in the other pillars would be 0.08 (=1/3/4) for the Learning to Do, 0.0625 (=1/4/4) for the Learning to Live Together, and 0.05 (=1/5/4) for the Learning to Be dimension. We allow a margin of ± 0.02 for the bounds. Therefore, we request that the contribution to the overall score of the indicators that belong to the Learning to Know dimension is between 3% and 7%, of the Learning to Do indicators is between 6% and 10%, of the Learning to Live together indicators is between 4.25% and 8.25%, and finally of the Learning to Be indicators is between 3% and 7%. Each region is therefore free to decide on the relative contribution of its indicators to the final score, so as to place the region in the best possible position in the ranking, while reflecting the lifelong learning-related priorities of that region. In other words, the DEA method assigns higher contribution to those indicators for which a region is strong and a lower weight to those indicators for which the region is comparatively weak. However, by assigning these bounds for the shares of the indicators, we ensure that each region includes all the indicators in each composite score and no particular dominance issue is raised (see relevant discussion in Section 3.2).

We run this analysis at the metropolitan area level ($n = 142$), instead of the community level ($n = 4576$) for ease of calculations. Table 17 summarises the "choices" (statistically speaking) of the metropolitan areas in Canada about each indicator's share in the composite indicator score. The first numerical column reports the average, over the 142 metropolitan areas, share of each indicator in the DEA-derived composite score. It provides the same type of information as the dominance analysis described previously for the CLI scores (see Table 7). This is in part due to DEA itself and in part due to the different spatial unit used for the analysis (metropolitan areas in the DEA, as opposed to communities in Table 7). It is interesting to note that the range of the shares is much more narrow than the one presented in Table 7. The greatest contribution to the DEA-derived composite scores comes from the *job-related training* indicator (9.2% of the index score, on average), followed by the *workplace training* and *charitable giving* (7.8%) and *distance to vocational training* (7.4%). The lowest contribution to the DEA-derived composite scores comes from the *distance to learning institutions* (3.8%) and the *university attainment* (4.0%).

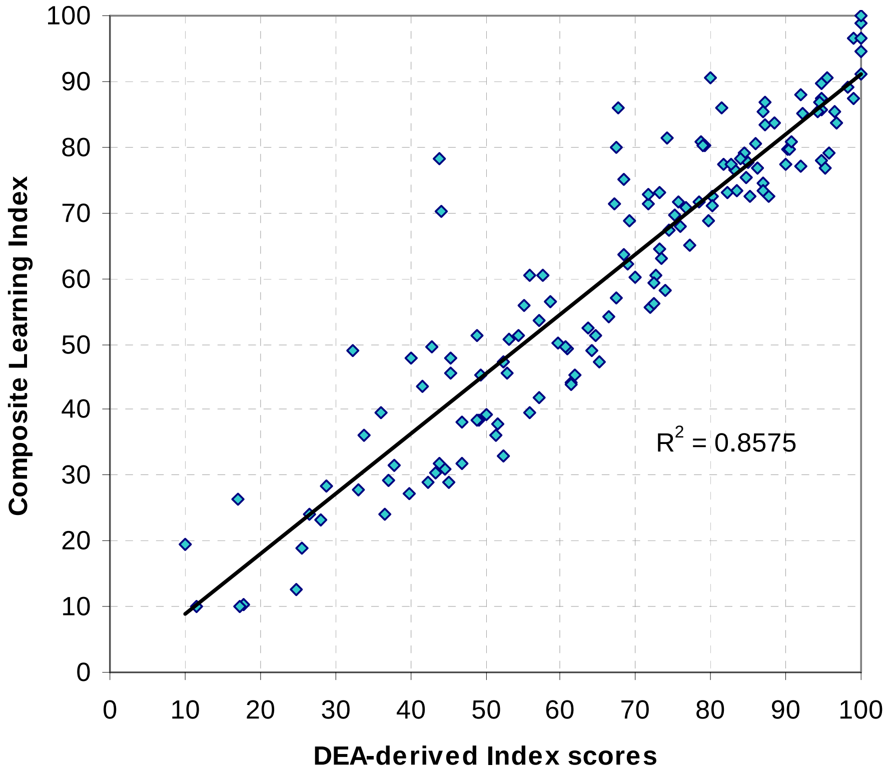
The second and the third numerical columns in Table 17 report the number of metropolitan areas in Canada that would choose to assign an indicator share equal either to the (allowed) lower or the upper bound. For example, to the *youth literacy skills* indicator, 44 metropolitan areas would assign a contribution of 3% (lower bound), whilst 76 metropolitan areas would rather give this indicator the maximum possible representation (7%) in their composite score. The remaining 22 metropolitan areas would let the share of the *youth literacy skills* indicator vary, so as to achieve the best possible position in the overall classification. It is interesting to note that more than 100 metropolitan areas give the lowest possible contribution to the indicators *university attainment, distance to learning institutions,* and *volunteering*. On the contrary, more than 100 metropolitan areas would rather assign the maximum allowed contribution to *job-related training*, *charitable giving*, and *participation in social clubs and organisations*.

Table 17. Statistics on the indicators shares to the DEA-derived scores

Lower and Upper Bounds for the shares	Indicator	Average share across the 142 metropolitan areas	Number of metropolitan areas with a share equal to the Lower Bound	Number of metropolitan areas with a share equal to the Upper Bound	Number of metropolitan areas with a share within the bounds
Learning to Know pillar	Youth literacy skills	5.6%	44	76	22
	PSE participation	5.5%	41	76	25
	University attainment	4.0%	100	25	17
[3% to 7%]	Distance to learning inst.	3.8%	103	14	25
	High school drop-out rate	5.2%	55	65	22
Learning to Do pillar	Job-related training	9.2%	18	103	21
	Workplace training	7.8%	72	52	18
[6% to 10%]	Distance to vocational training	7.4%	87	39	16
Learning to Live Together pillar	Charitable giving	7.8%	12	122	8
	Volunteering	4.5%	127	2	13
	Participation in social clubs, etc	7.5%	20	100	22
[4.25% to 8.25%]	Distance to Community Inst.	6.1%	67	57	18
Learning to Be pillar	Exposure to media	5.3%	54	72	16
	Learning through sports	4.5%	85	47	10
	Learning through culture	5.7%	31	83	28
[3% to 7%]	Distance to cultural resources	5.1%	59	65	18
	Broadband internet access	5.0%	67	63	12

Upon granting leeway to each metropolitan area in the assignment of the shares, whilst respecting the relative upper and lower bounds, the DEA-derived scores present a strong association with the CLI scores ($R^2 = 0.86$) (Figure 7). This result shows that even if an area-specific weighting scheme would have been employed to build the CLI, as opposed to a fixed set of weights for all metropolitan areas (or communities, etc), the picture on the state of learning in Canada would not have been affected substantially.

Figure 6. Relationship between the CLI scores and the DEA-derived composite scores

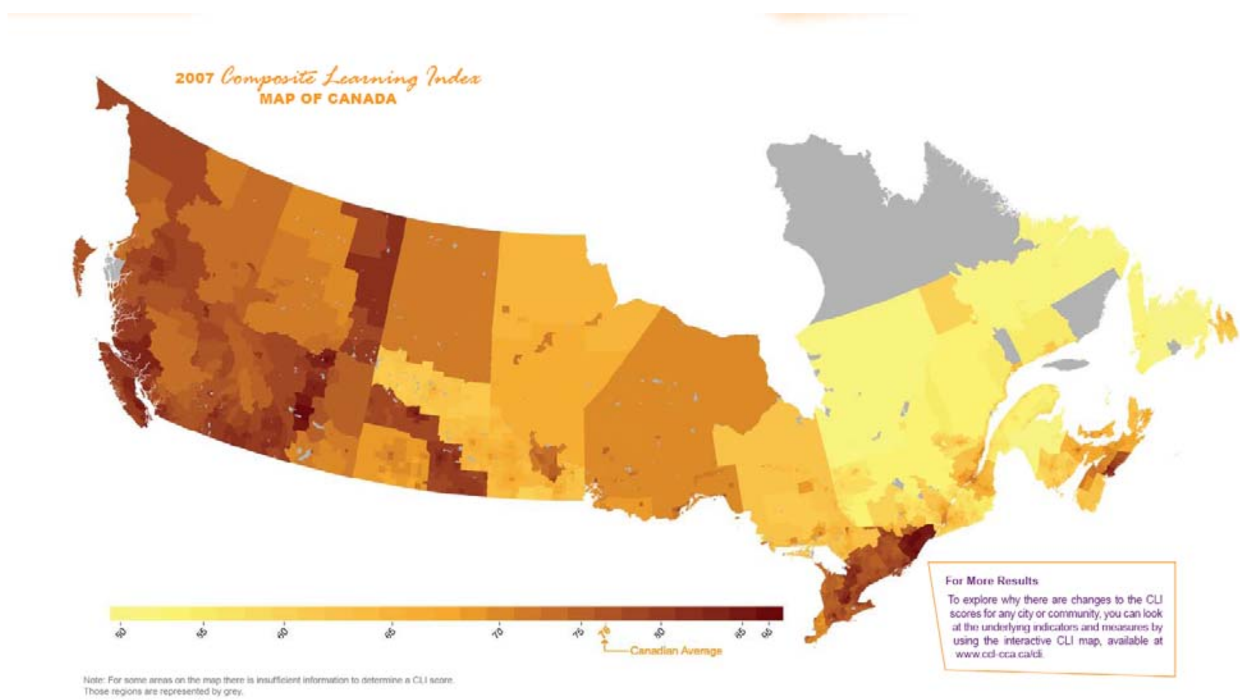


Note: For the purposes of this comparison the scores for 142 metropolitan areas are scaled in the [10, 100] range.

Having carried out a robustness assessment of the CLI and shown that the results provide, in most cases, reliable estimates of the lifelong learning status in Canada, we show next how the CLI can be used to extract data-driven narratives on the issue, going beyond the information provided already by the Canadian Council on Learning in its relevant report (Canadian Council on Learning, 2007).

The CLI results provide fertile ground for the analysis of lifelong learning performance in Canada. The CLI scores (Figure 7) from the original report represent the state of learning in cities, regions and communities across Canada. A high CLI score means that a particular city or community possesses learning conditions that support economic and social success. Although not the sole factor contributing to such success, lifelong learning is increasingly important in the global, knowledge-driven economy. While a community will score higher than some and lower than others, the purpose of the CLI is not to identify winners and losers. Instead, the CLI is intended to generate a discussion about what factors contribute to the best possible learning environment. After all, key to successful lifelong learning is the ability to cooperate with and learn from others.

Figure 7. 2007 Composite Learning Index scores for Canada

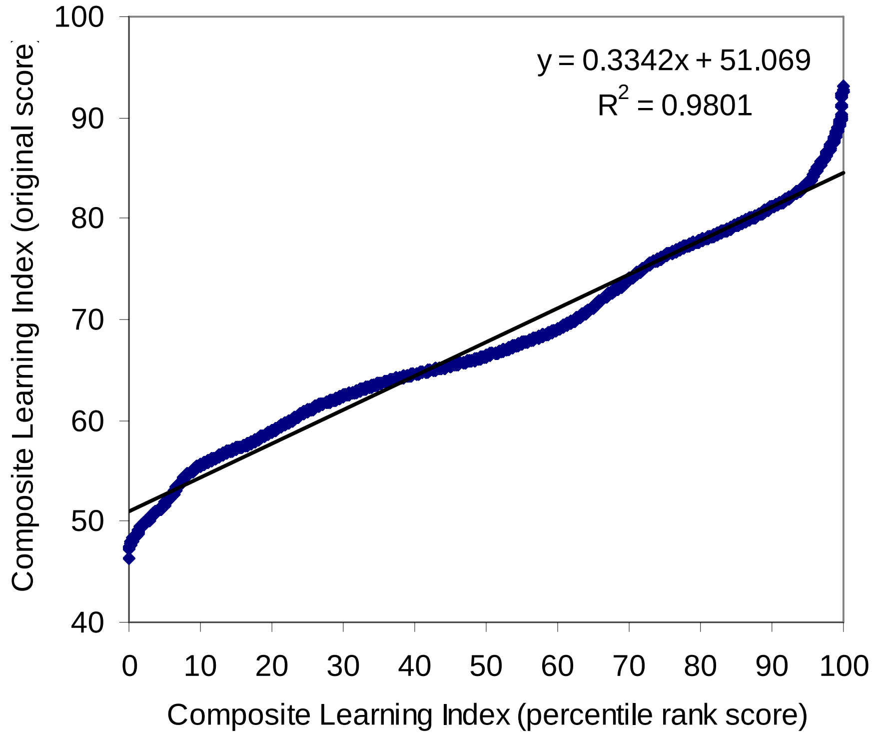


Note: Figure from "The 2007 Composite Learning Index" report.

The relation between the CLI original scores and the percentile rank score for the 4576 communities in Canada is shown in Figure 8. It is interesting to note the high degree of linearity between the two series, with exceptions at the two very-ends of the distribution. A

5-point increase in the CLI score implies creating better lifelong learning conditions than 15% more communities compared to the situation before the improvement. This change would be less evident if a community is at the very-low or very high end in the CLI ladder .

Figure 8. 2007 Composite Learning Index scores and percentile ranks scores



6.1 Exceptional behaviour of some Canadian communities

The CLI shows that there is no ideal community in Canada, among the 4576 studied, excelling in all 17 indicators of learning, but that there is space for improvement at all levels of lifelong learning. Interestingly, the top CLI scores do not belong to the communities of a single province. Several communities mostly from Ontario, Saskatchewan and Alberta share a pie in the “best practices cake” of lifelong learning conditions. On the other hand, neither do the communities that lag behind come from a single province.

Given that the aim of this entire analysis is not to name and shame, but rather to spot the light on where things go well and where things could be improved, we will discuss the results accordingly.

Canadian communities that have a high performance in the overall CLI have generally high performance in all four pillars of learning. The reverse, however, is not necessarily observed. To see this more clearly, we grouped the communities in terms of their percentile rank in four quartiles of the CLI and four quartiles for each pillar. The resulting

4×4 matrix per pillar is shown in Table 18. Exceptional behaviour is captured by non-zero numbers in the upper right and low left part in each matrix, where communities have top CLI performance but low performance in one of the pillars, or vice versa. Furthermore, a symmetrical behaviour with no surprises would imply that the numbers in the main diagonal of each matrix are the highest in the row. As we suspected, the map of Canada on lifelong learning has several surprises to reveal.

In the Learning to Know pillar, 14.6% of the communities have top 25% performance both in the CLI and in this pillar. On the other end, we find 9.1% of Canadian communities with bottom25% performance in both the CLI and in this pillar; the remaining 15.9% of the bottom25% performers in Learning to Know do well in the other three pillars of learning and thus have good CLI performance. Surprisingly, only 11 communities (0.2%), all from the Saskatchewan province, have high CLI performance but particularly low scores in Learning to Know. However, these communities are particularly strong in the Learning to Be pillar and have good performance in the Learning to Do and the Learning to Live together. On the other end, 58 communities (1.3%) from Quebec have bottom25% CLI performance, but top25% performance in Learning to Know. Their challenges are in the other three pillars of learning, which explains their low CLI performance. The mid-range performers in this pillar also have a medium CLI performance. As for the Learning to Do pillar, there are no peculiarities to report and the level of performance follows that of the CLI. The Learning to Live Together pillar has a few exceptions to reveal. Six communities (0.1%) are on top of the CLI ladder, but they are particularly weak in the Learning to Live together pillar. These communities do not belong to a single province, but are located in Ontario, Alberta and British Columbia. Mirror pattern is also found in six communities from New Brunswick, Quebec and Saskatchewan, where weak CLI performance is coupled with top performance in Learning to Live together. Finally, in Learning to Be, there are no surprises, and the pattern is as expected: high performers in this pillar have high CLI performance, and so forth. Similar pattern was found previously for the Learning to Do pillar. However, the Leaning to Be pillar reveals a further message: top CLI performance is achieved almost exclusively by communities (21.7%) with top performance in Learning to Be, because communities that are strong in Learning to Be are also strong in at least two more pillars of learning. This was not observed for any of the other three pillars of learning.

Table 18. Comparison of the CLI scores versus the four pillars of learning

		Composite Learning Index			
		Bottom25%	25-50%	50-75%	Top25%
Learning to Know	Bottom25%	9.1	9.4	6.3	0.2
	25-50%	8.0	5.7	7.3	4.1
	50-75%	6.7	7.3	4.9	6.1
	Top25%	1.3	2.7	6.5	14.6
Learning to Do	Bottom25%	21.0	3.0	1.1	0.0
	25-50%	3.8	15.2	5.8	0.1
	50-75%	0.2	5.6	12.2	7.7
	Top25%	0.0	1.2	6.0	17.2
Learning to Live Together	Bottom25%	16.0	7.4	1.5	0.1
	25-50%	7.2	6.8	7.5	3.5
	50-75%	1.6	6.4	6.9	10.1
	Top25%	0.1	4.3	9.2	11.3
Learning to Be	Bottom25%	19.8	4.7	0.5	0.0
	25-50%	5.2	13.1	6.7	0.1
	50-75%	0.1	7.2	14.5	3.2
	Top25%	0.0	0.0	3.3	21.7

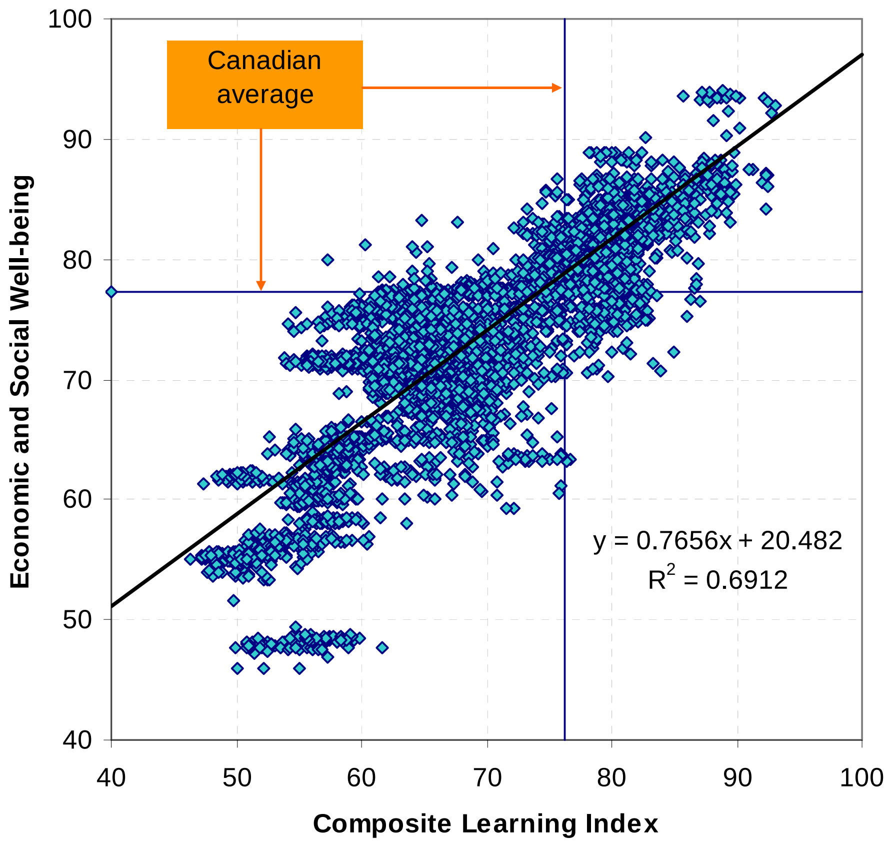
Note: Numbers indicate the % of communities (n = 4576) that belong to a given combination of quartiles.

6.2 CLI scores and economic/social outcomes of learning

The CLI was built bearing in mind both the underlying indicators of learning and the economic and social benefits of learning, such as income, employability, population health, voters' participation, adult literacy and early childhood development. These outcomes are often perceived as components of a society's well-being and are used in this Section to study the link between lifelong learning conditions, as estimated by the CLI, and a society's economic and social welfare.

Figure 9 presents the relationship between the original CLI scores (taken from the CCL-CLI website) and the ESWBI scores. The results show a significant and high linear relationship between lifelong learning conditions and the economic and social well-being in Canada (r^2 = 0.698, n = 4576). At the lower end of well-being, about 110 communities score less than 50 points in the ESWBI and have low performance in the CLI, too. All these communities belong to two Provinces, Newfoundland & Labrador and Quebec. Mid-way, there are communities that despite their high level of ESWBI do not perform as high as expected in the CLI, and vice versa. Although correlation does not imply causality, and the latter cannot be tested in the Canadian dataset due to lack of timeseries, these results are consistent with the theory that lifelong learning translates into a more efficient use of an economy's human resources, in terms of employment, civil engagement, adult literacy and thus affects the overall productivity and economic performance in Canada. The high number of communities that was used for this analysis (*n* = 4576) supports further this argument.

Figure 9. CLI versus economic and social well-being in Canada



Note: original scores taken from the CCL-CLI website

Comparison of the performance of communities in the CLI and in ESWBI shows that more than 22% of the top25% CLI performers have top25% performance in the ESWBI (Table 19). On the other end, only half (12.4%) of the bottom25% performers in the CLI are bottom25% performers in the ESWBI. The remaining 12.1% is split, almost exclusively, between the 25-50% and 50-75% performers of ESWBI. This implies that very high performance in the CLI is a sufficient, though not necessary, condition for high performance in the ESWBI. In fact, a couple of communities in Canada, Sheffield (in New Brunswick) and Longue-Pointe-de-Mingan (in Quebec) are relatively weak in all pillars of learning and in the CLI, but they do very well economically and socially. This shows that these two communities have other means of achieving learning success, which is not entirely captured by the learning indicators included in the conceptual framework.

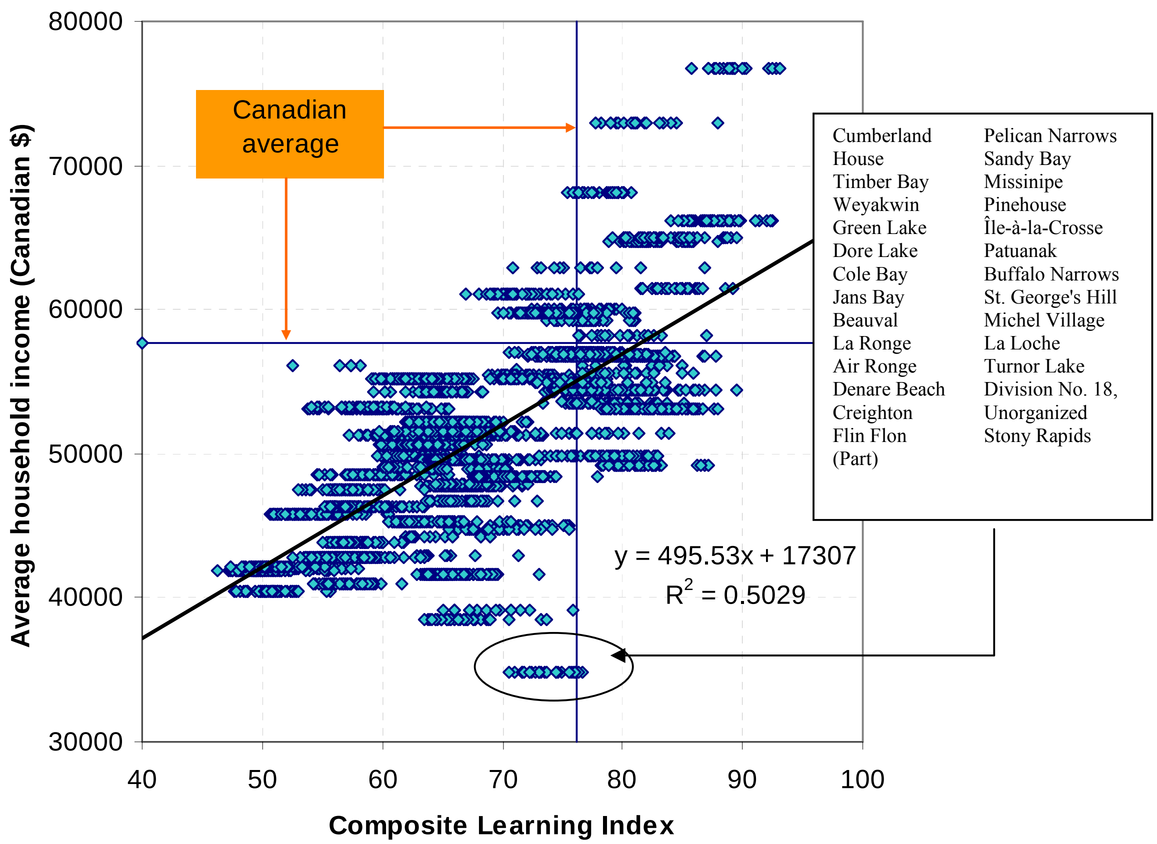
Table 19. Comparison of the CLI scores versus the ESWBI scores

ESWBI (Economic and Social Well-being Index)	CLI (Composite Learning Index)			
	Bottom25%	25-50%	50-75%	Top25%
Bottom25%	12.4	0.2	0.2	0.0
25-50%	6.3	1.6	1.7	0.0
50-75%	6.3	21.6	13.6	2.4
Top25%	0.1	1.6	9.6	22.6

Note: Numbers indicate the % of communities (n = 4576) that belong to a given combination of quartiles.

A last remark before concluding this analysis on the link between the CLI and the economic and social outcomes of learning. Figure 10presents the scatterplot of the average household income level versus the CLI and presents a relatively good degree of linearity ($r^2 = 0.508$). It shows that 10 points increase in the CLI score is associated with, on average, 10000 Canadian $ of extra annual income. It is interesting to note that about 26 communities (listed in Figure 10) have very good performance in the CLI (scores in the range 70-77), but the average annual income is the lowest in Canada (less than 35000 Canadian $). To those communities, which are belong to the Saskatchewan province, the very good lifelong learning conditions have resulted in very high adult literacy rates and very low unemployment rates, although the annual household income has remained very low. The widest spread of CLI scores is observed at annual household income of 53000 Canadian $. Communities at this income level score from as low as 53 to as high as 88 in the CLI. Those communities with CLI scores close to 53 have not succeeded socially, as opposed to their counterparts, in terms of income level, which have a CLI score close to 88 and have succeeded both economically and socially. These results provide a further proof that the lifelong learning conditions in Canada, as measured by the CLI, go beyond income benefits, and capture other aspects of the quality of life related to social benefits.

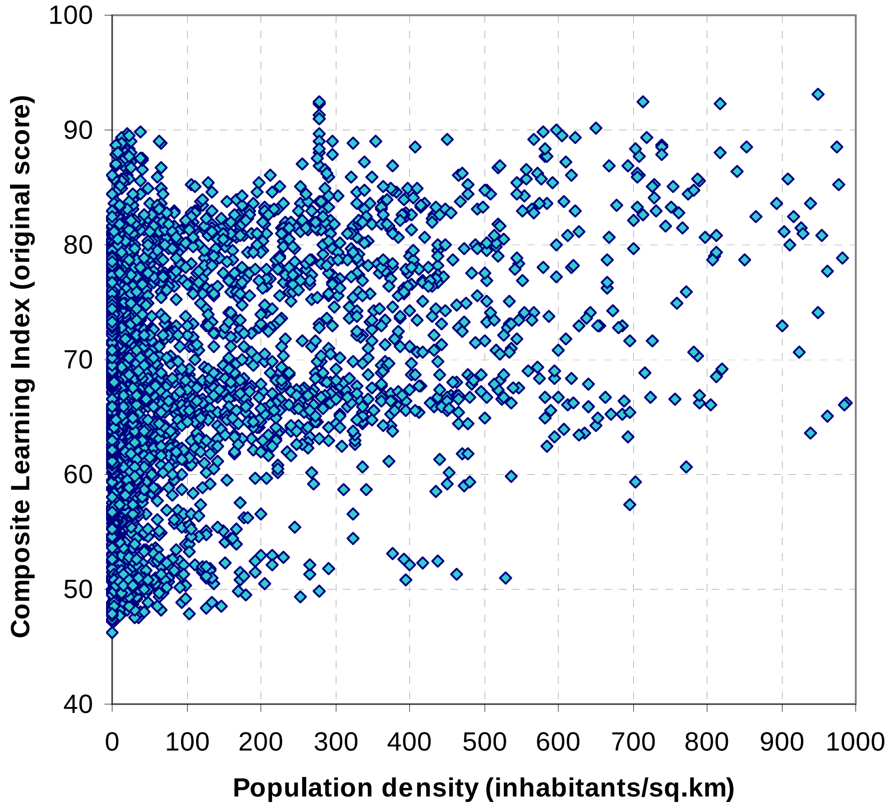
Figure 10. Scatterplot between the CLI and the average household income



6.3 CLI and population relates aspects

A community with numerous population may face eventual difficulties in learning-related infrastructure capacity that does not suffice to cover the needs of its population. On the other hand, a low populated density maybe associated with high distances within the community, thus a low performance in the distance-related indicators included in the CLI framework. However, the correlation between the CLI scores and the population density across the 4576 Canadian communities (Figure 11) shows the association between the two is almost random. This result shows that population density is not a destiny in lifelong learning as conceptualized in the CLI framework.

Figure 11. Relationship between the CLI and the population density



Next we touch upon inequality issues related to the dispersion of the lifelong learning conditions in Canada. There are many ways of measuring inequality, all of which have some intuitive or mathematical appeal (Amiel and Cowell 1999, Litchfield 1999, Atkinson 1970, 1983, Cowell 1980, 1985, 1989, 1995, 1999, Dalton 1920). Of the vast literature on such measures, applied in particular to measure income inequalities, we have selected the Gini coefficient (Gini 1912, 1921, Dorfman 1979, Gastwirth 1972) as the basis for our approach. We propose to estimate a "CLI coefficient" that could be used as an inequality measure of lifelong learning conditions across Canada.

We first build the CLI curve, which is the product of the community CLI scores, in increasing order, multiplied by the community population (cumulative, %). Next, we plot the CLI curve versus population (cumulative, %). The CLI coefficient is finally calculated as a ratio:

$$CLI_G = A/(A+B)$$

where A: is the area between the CLI curve and the uniform distribution line and B is the area under the uniform distribution line.

A low CLI coefficient value indicates more equal lifelong learning conditions (best case 0), while a high CLI coefficient value indicates more unequal conditions (worst case 1). Since A+B = 0.5,

$$CLI_G = A/0.5 = 2A = 1-2B$$

If the CLI curve is represented by the function $y = CLI(x)$, where x is the cumulative proportion of the population, and y is the cumulative proportion of the CLI, the value of B can be found with integration:

$$CLI_G = 1-2\int_0^1 CLI(x)dx$$

In practical terms, we approximate the CLI curve, on each interval, as a line between consecutive points and thus the area between the CLI curve and the perfect equality curve can be estimated by summing the surfaces of the trapezoids. The CLI coefficient is given by:

$$CLI_G = 1-\sum_{k=1}^{n}(x_k - x_{k-1})(y_k + y_{k-1})$$

where x_i is the cumulative proportion of the population, for $k = 0,...,n$, with $x_0 = 0$, $x_n = 1$ and y_i is the cumulative proportion of the CLI, for $k = 0,...,n$, with $y_0 = 0$, $y_n = 1$ and n is the number of trapezoids.

There are several advantages of using the CLI coefficient as a measure of inequality.

- It is a measure of inequality by means of a ratio analysis and it is based on the entire CLI curve, rather than a value averaged over the entire population.
- It can be used to compare lifelong learning conditions across different population sectors (e.g. rural or urban areas) as well as countries and it can be easily interpreted.
- It can be used to indicate how lifelong learning conditions have changed within a country over a period of time, thus it is possible to see if inequality in knowledge is increasing or decreasing.
- It satisfies two important principles: (a) *Anonymity*: it does not matter who the high and low performers on lifelong learning are. In fact, all that counts is the CLI curve. (b) *Scale and population independence*: it does not matter how big a country is, or how large the population of the country is. These conclusions are based on the independence of the CLI scores from the population density, discussed above.

However, there are three important considerations to be made regarding the potential of using the CLI coefficient as a measure of inequality of lifelong learning conditions. First, the CLI coefficient varies when the distribution varies, no matter if the change occurs at the top or at the bottom or in the middle. To this end, it is important to report both the CLI coefficient for Canada, together with the CLI scores for the communities or regions. In fact, the CLI coefficient is proposed as a complementary tool to the CLI.

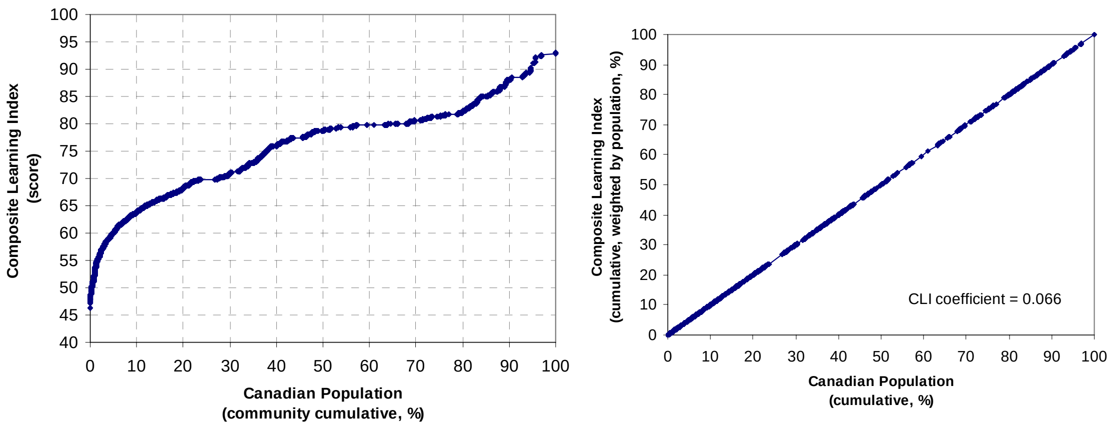
Second, the CLI coefficient needs to be reported together with the proportions of the quantiles that were used for its calculation. As with other inequality coefficients, the CLI coefficient is influenced by the granularity of the measurements. For example, five 20% quantiles (low granularity) will usually yield a lower CLI coefficient than twenty 5% quantiles (high granularity) taken from the same distribution.

Third, the CLI coefficient is not additive across groups, i.e. the total CLI coefficient of a society is not equal to the sum of the CLI coefficients for its sub-groups. In fact, the CLI coefficient for an entire country would be much higher than those of its regions individually. For this reason, if an attempt is ever made to develop a lifelong learning index for the European countries, it should not be the CLI coefficients for individual countries to be compared with that of the entire Canada, but the overall value for the EU.

Upon these brief theoretical considerations, we calculated the CLI curve for the Canadian communities using twenty 5% quantiles (high granularity). Figure 12b shows that the CLI curve is very similar to the perfect line of equality. In fact, 50% of the Canadian population is on the 45.4% of the CLI curve (ideal value 50%) and 90% of the Canadian population is at the 88.9% of the CLI curve. Overall, the CLI coefficient for Canada is $CLI_G = 0.066$. This is a first, and suggestive, attempt to create a measure of dispersion of lifelong learning conditions across Canada and given the lack of a benchmark, no comparison to other countries, such as the EU or the U.S.A can be made. However, the same inequality measure can be calculated for each of the four pillars of learning. The inequalities across the population for the pillars of learning are higher compared to those of the overall CLI, yet not pronounced ($KNOW_G = 0.110,\ DO_G = 0.104,\ LIVE_G = 0.116,\ BE_G = 0.103$).

The work on the CLI coefficient presented here is preliminary and thus not conclusive. Yet, it gestures towards the need for further research on the topic, which however, seems to be worth the effort.

Figure 12. Overall lifelong learning conditions and population

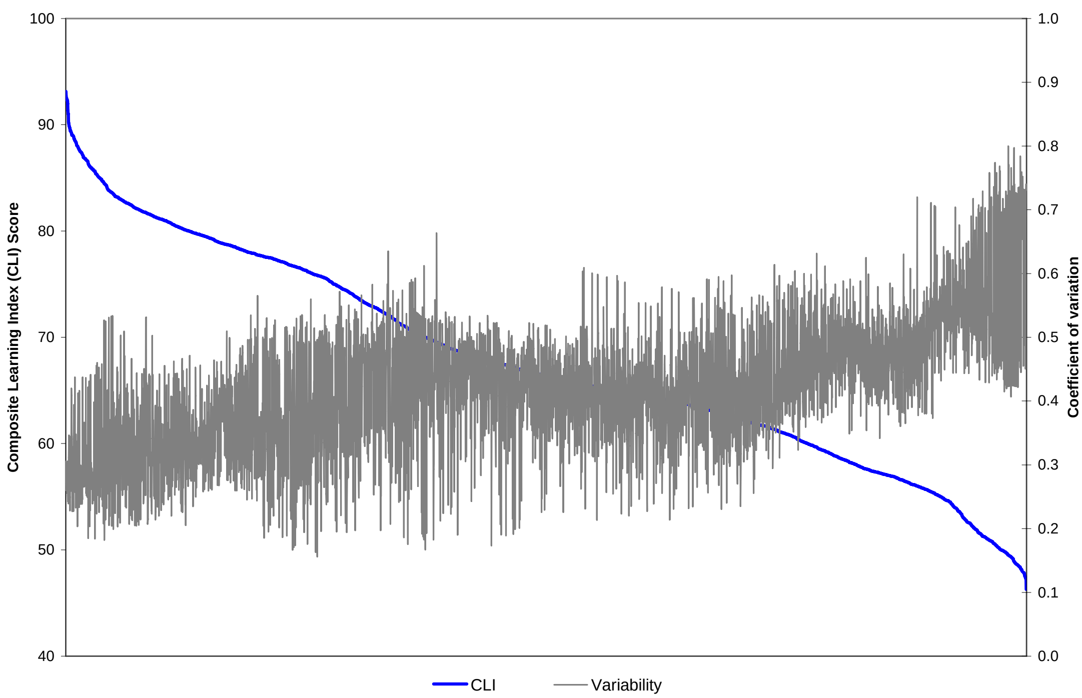


(a) (b)

Concluding this section, we discuss the relationship between the CLI scores and the variability in the set of 17 underlying indicators composing the CLI. The Canadian communities that are situated high or mid-way in the CLI range tend to score uniformly high in the various indicators of learning. In other words, these communities display a relatively low variability, which equals the coefficient of variation, across the 17 indicators values for a given community. In order to calculate the variability, the indicators were scaled using the Min-max approach since the standardisation method would tend to underestimate the variability. Figure 13Figure 13 shows that the variability increases as one moves down the list in decreasing order of CLI scores. This scissors pattern is evident, yet not pronounced. The correlation coefficient between the CLI and the coefficient of variation series is equal to $r = -0.63$, indicating *a moderate degree of reverse association between the CLI scores and the variability in the underlying indicators*. For comparison purposes, in the case of the Trade and Development Index (UNCTD, 2005) that is based on eleven components and developed for 110 countries, the correlation coefficient between the index scores and the coefficients of variation series was much higher and equal to $r = -0.93$.

An implication of this finding is that while changes in the CLI scores over time could be regarded as a quantitative indication of trends in lifelong learning performance in Canada, those in respect of the variability could be seen as qualitative changes. Reducing even further the variability in the indicators should be among the objectives of lifelong learning policies and strategies in Canada. To be successful, a Canadian community must put simultaneous thrust on multiple goals within a coherent lifelong learning strategy, while emphasizing reduction of the existing gaps in areas where performance is lagging. As the exceptional behaviour of a few communities indicates, communities which have very low CLI performance but very high performance in just one or two pillars of lifelong learning (see results in Table 18), a disproportionate emphasis on a limited number of objectives without concomitant focus on many of the determinants of lifelong learning can yield only marginal results. By demonstrating significant inter-community differences in the values of the coefficient of variation, the scissors diagram (Figure 13) points to the importance of community-specific approaches to lifelong learning strategies. At the same time, though, there is no way that these variations will be reduced without coherence between lifelong learning policy and rule making, on the one hand, and lifelong learning strategies and partnership and solidarity, on the other.

Figure 13. The scissor diagram of CLI and variability

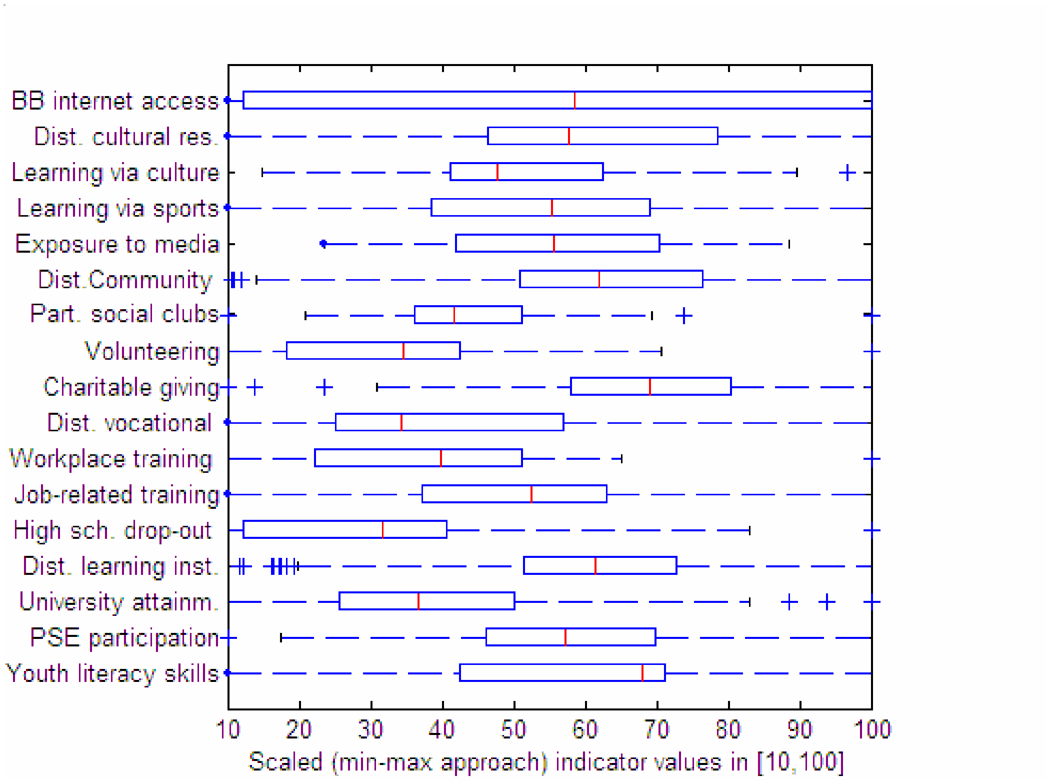


6.5 Proximity to long-term targets

Besides looking at variations in the indicators, an examination of the proximity-to-target distances of the Canadian communities in each of the 17 indicators of the CLI framework may provide insight into the nature of policy challenges from the perspective of lifelong learning. As targets in this section, we consider the long term targets, which are equal to the maximum value of each indicator across the communities (see Table 10).

Figure 14 portrays the distribution (across the 4576 communities) of proximity-to-target scores for the 17 indicators. There are ten indicators, in which half of the communities are mid way or even closer to the long-term target. Particularly worrying is the performance of the Canadian communities in the remaining seven indicators: *participation in social clubs* *and organizations, volunteering, distance to vocational training, workplace training, high school drop out,* and *university attainment.* These indicators represent distinct and difficult policy challenges, as they are related to the individuals' behavior, except for the *distance to vocational training*. Here, the challenge of regional bodies is to create incentives to promote volunteering, and attract people's interest in completing high school and participating in university programs. At the same time, it is a responsibility of the local authorities to create vocational training (schools, business and secretarial schools) available at a close distance to the majority of the Canadian citizens.

Figure 14. Box plot of the proximity-to-target scores for the 17 indicators of learning



Note: a box has lines at the lower quartile (25th percentile), median (red line), and upper quartile values (75th percentile); whiskers extend from each end of the box to show the extent of the rest of the data; Outliers (+) are data with values beyond the ends of the whiskers.

7. Conclusions

Learning is much more than academics and the Composite Learning Index (CLI) provides a comprehensive vision of learning. Made up of 17 indicators (24 metrics), the index takes into account factors as diverse as distance to learning institutions, services and resources, availability of workplace training, learning through sports and culture, volunteering and youth literacy to compile a profile of communities and, ultimately, the country. The indicators were selected by the Canadian Council on Learning (CCL) following expert consultation to fill in a four-pillar framework originally proposed by UNESCO:

(a) *Learning to Know* (knowledge acquired in the classroom),

(b) *Learning to Do* (knowledge acquired at work),

(c) *Learning to Live Together* (knowledge acquired in the community),

(d) *Learning to Be* (knowledge acquired at home, or family).

The methodological approach used to construct the 2007 CLI was studied extensively in this report. Additionally, with a view to highlight several issues on the lifelong learning conditions in Canada, examples of data-driven narratives were provided together with their implications for policymaking. We dedicate the following two sections to summarise the methodological and data-driven narratives, respectively.

7.1 Methodological issues on the CLI

An appealing and concise way to present the CLI is given in Table 20. This table provides information on the conceptual framework used to support the construction of the index, the main objectives of the index, information on the data (sources, timeframe, variable selection, indicators, thematic dimensions), information on the methodology (index formulae, transformation of data, normalization, weighting and aggregation issues, sensitivity analysis) and, finally, information on the output (unit, range of scores).

The robustness assessment of the CLI by means of multivariate analyses, dominance analysis and sensitivity analyses revealed no particular shortcomings in the index structure.

Factor analysis applied to the seventeen indicators of the CLI framework revealed the presence of a strong correlation structure in the dataset and corroborated its multi-dimensionality. Given the large number of Canadian communities used in the analysis ($n = 4576$), the correlations were not considered spurious. The indicators share six common (unobserved and uncorrelated) factors that explain almost 80% of the variance of the full set.

However, the six factors do not have an intuitive interpretation. Neither when extracting four common factors, with a view to resemble the four-pillar structure, is it straightforward to interpret the factors. It was, thus, preferred to use the UNESCO four-pillar framework as it proposes four forms of lifelong learning, at home, in the classroom, at work and in the community. Factor analysis within each pillar indicated that the underlying indicators in each pillar are not redundant, yet partially overlapping and not entirely separable. Measurement error due to the different spatial resolution of the data reported from national statistical offices was incorporated in the correlation structure.

The impact of an underlying indicator on the CLI was assessed in various ways: by means of standardized regression coefficients, eliminating one indicator at-a-time and finally analyzing the share of each indicator score on the CLI score. All three approaches showed that the impact of the indicators (or pillars) to the CLI scores is not equal between them. That would neither be expected nor desired. More important conclusion from these analyses is that the CLI scores are not dominated by a small number of indicators. Instead, eight indicators contribute, on average, by more than 5% to the CLI scores, and four of them have a contribution of at least 10%. Parsimony in the development of the index would have suggested excluding those indicators from the CLI framework that do not have an important impact on the results. However, literature suggests that it may not be advisable to exclude indicators from an index based merely on statistical evidence, unless excluding certain indicators is supported by expert opinion on the relevance of the indicators to the issue. Given that these indicators derived from expert consultation, it was decided to keep all the indicators in the dataset. An eventual revision of the framework in a few years time may be undertaken, when available time series would allow a thorough study of the causal links between the lifelong learning indicators.

Sensitivity analysis using twenty-five methodological scenarios (all with their advantages and implications) showed that, for the vast majority of the Canadian communities, the CLI scores are reliable and not particularly sensitive to changes in the normalisation method or the weighting method or the pillar structure. The use of non-compensatory aggregation and geometric aggregation further reinforces this message, given that results are in general not dependent on the aggregation method used. The use of data envelopment analysis, which allows for the identification of region-specific weights, shows that the DEA-derived scores present a strong association with the CLI scores ($R^2 = 0.86$). This result shows that even if an area-specific weighting scheme would have been employed to build the CLI, as opposed to a fixed set of weights for all metropolitan areas (or communities, etc), the picture on the state of learning in Canada would not have been affected substantially. However, the analysis spotted about eighteen communities whose CLI score is very sensitive to the methodological assumptions in the index. Thus, any message conveyed by the CLI for those communities should be formulated with great caution and be considered as only indicative or suggestive. The median score across the scenarios was considered as an unbiased "summary picture" of the lifelong learning conditions in Canada. The correlation between the CLI and the median is very high (R^2=0.899, p<0.001, n=4576). This result shows that the CLI provides an unbiased summary picture of the lifelong learning conditions in Canada and that it is representative of a plurality of methodological scenarios. Caution, however, is required when discussing the CLI scores for about 150 communities (out of 4576), for which the CLI score deviates significantly from the median score. Every statement on the lifelong learning conditions, as estimated by the CLI, for those communities needs to be made with caution, indicating that the results are merely indicative. For the remaining communities, the CLI scores can reliably be used for policy-making or for benchmarking purposes.

In order to better understand the phenomenon of lifelong learning, the relationship between the CLI and other social and economic indicators was explored. We found that, compared to the scenarios, the CLI has the strongest association to the aggregate of the economic and social outcomes of learning (r =0.84) and to the adult literacy (r =0.75). Both these indicators/indices were used for the external validation of the CLI and its alternatives.

Cluster analysis generated four clusters that can help local authorities look beyond geographic peer groups or other type of classification in order to identify models of lifelong learning success from areas facing similar challenges. Going over the mere identification of clusters, our aim was to provide cluster-specific targets for the 17 indicators of learning, which could be reached in the short-term by the metropolitan areas, before such areas would engage themselves in efforts to reach longer term targets. The results further showed that the selected indicators are able to distinguish between the lifelong learning conditions of the Canadian metropolitan areas and that the CLI reflects, without distorting, the information content in the dataset.

Table 20. 2007 Composite Learning Index- A summary profile

Conceptual framework	Combination of framework (Delors' Task Force) and Canadian data availability
Purpose	▪ Facilitate cross regional comparisons in Canada ▪ Monitor progress ▪ Provide analytical tool for prioritization and policy making ▪ Operationalise a conceptual framework ▪ Map Canadian patterns of lifelong learning ▪ Stimulate discussion on what can be done to improve the quality of learning across all age groups
Representative	Highest resolution: 4576 communities. Results provided also for metropolitan areas, cities, provinces
Data	
Sources	Public and internal calculations (distance-related indicators)
Timeframe	2005-2006, yearly averages
Variable Selection	Expert opinion and correlation analysis
Indicators	17 (based on 24 metrics)
Thematic Dimensions	4 (Learning to Know, Learning to Do, Learning to Live Together, Learning to Be)
Methodology	
Index Formulae	$CLI = w_1 \sum_{i=1}^{5} w_{Know,i} \cdot I_{Know,i} + w_2 \sum_{i=1}^{3} w_{Do,i} \cdot I_{Do,i} + w_3 \sum_{i=1}^{4} w_{Live,i} \cdot I_{Live,i} + w_4 \sum_{i=1}^{5} w_{Be,i} \cdot I_{Be,i}$
Transformation	Directional adjustments (indicators with opposite direction than the desired one where transformed by: *1-value*)
Normalisation	z-scores (subtracting the mean and dividing by the standard deviation)
Missing values	Estimation: no missing values allowed
Aggregation levels	3 (Level 1:Metrics to indicators, Level 2: indicators to pillars, Level 3: pillars to Index)
Weights	Statistically-driven based on a combination of Factor analysis and multivariate regression analysis (independent variable: economic and social outcomes of learning)
Aggregation	Average value (1st level) Weighted summation of main principal factors (2nd level) Weighted summation of principal factors (3rd level)
Sensitivity Analysis	Extensive (indicators, normalisation, weighting, aggregation, pillar structure)
Output	
Unit	Unitless
Range of scores	Best performance achieved: 93 points Weakest performance achieved: 46 points Average (Canadian level): 76 points
Editions	Second Edition since 2006

A further note on this issue is in place. Uncertainty and sensitivity analyses were used *during* the construction of the CLI. By doing so, initially subjective design choices have been corrected, modified, and ultimately justified, with a view to increase the reliability of the results. The CCL-CLI team took into account the feedback provided by the application of uncertainty and sensitivity analyses on the CLI and moved from a one-way design process to a circular approach. At first, an initial set of about 35 indicators underwent multivariate analysis to identify indicators that were highly correlated. This information was then fed back to either remove or sum up highly correlated indicators. This approach was applied for example to the three PISA-related indicators measuring reading, math and problem solving skills. Given that the bivariate correlation between them was very high ($r = 0.85$), the three variables were simply averaged to produce the *youth literacy skills* score. In subsequent design steps (e.g. indicator grouping, aggregation or weighting), uncertainty and sensitivity analyses provided decision-support and guided the exploration and selection of various design options. This process was followed with a view to set the foundation for a balanced index from the start.

In brief, the analyses have demonstrated that the Composite Learning Index

- is internally robust,
- corrects for relationships between indicators (no double counting of information),
- has no strong dominance of few indicators, but a rather balanced structure,
- provides results that are not strongly affected by compensability issues among the underlying indicators,
- can withstand external validation by proxy measures of lifelong learning, such adult literacy and other economic and social benefits of learning,
- is representative of a plurality of alternative methodological scenarios, and
- is essentially a weighted average of seventeen indicators: a form that is easy to communicate to the wider public. Yet, the statistical approach to estimate the weights may be harder to be understood by a non-statistically literate audience.

The CLI, having passed the "statistical" filters of index quality, it can be reliably used to measure lifelong learning across Canada, identify weaknesses, and propose remedial actions. The CLI can serve for easy spatial and temporal comparisons (benchmarking) to prioritize areas in Canada of relatively low lifelong content, monitor and evaluate policies effectiveness and ultimately to funnel resources to provinces through, for example, multilateral and bilateral agreements between Canadian cities.

Three important caveats are necessary before concluding the methodological issues summarised here. The first and most obvious is that the conclusions of the CLI depend primarily on data availability. Important indicators could be poorly or not at all represented. Furthermore, lifelong learning is an evolving concept, therefore some important indicators of lifelong learning may be missing from the theoretical framework.

The second remark relates to the fact that distance to learning institutions, or cultural resources, etc, does not guarantee actual participation in such institutions. However, a 2002 study by Statistics Canada indicates that high-school graduates who live beyond commuting distance to a college or university are less likely to participate in those post-secondary institutions. This was especially the case for students from low-income families. A similar study from the United States reveals that students attained, on average, one year less schooling if they resided in a community where there was no college nearby. It appears therefore, that large distances may act as a prohibitive factor to actual participation in those institutions, whilst short distances may not guarantee actual participation. Given this reasoning, the CLI approach to use distance measures as proxies for participation were justified, but future work, within the context of the annual CLI revision, needs to address in depth this issue.

The third and last remark in this context. The analysis undertaken in this report provides no indication of the true ability of the CLI to capture lifelong learning. Yet, it provides enough evidence that the CLI, tailored to the specific needs of the Canadian reality and diversity in lifelong learning, can not be easily falsified.

7.2 Messages conveyed by the CLI

The real value of the CLI lies not in the overall classification of the communities. When evaluating different communities in Canada, it is unavoidable that some of them appear at the bottom and some at the top of the CLI classification. Yet, this does not mean that communities with low CLI scores are weak, or that the top performing communities need not make any further effort. In absence of a national or international benchmark for lifelong learning, only the relative performance of the different Canadian communities can be assessed. The issue is then whether it is actually possible to create a normative national benchmark for lifelong learning. We believe not, since lifelong learning has to do with culture, history and the organisation of human activities in a particular Canadian community or province, and diversity is a reality to be accepted. In fact, it is not by negligence that the CLI results are not provided in any form of ranking, though this could be done by the public itself. Instead the CLI results are provided in alphabetical order of the constituencies studied (e.g. cities, communities, metropolitan areas, etc).

The CLI is itself a learning tool. It is meant to serve as a starting point for analysis and discussion, to get people thinking about different ways of learning, how they can learn more effectively and how they can learn from other communities across the country. As a tool for informing policy decisions, the CLI facilitates monitoring of lifelong learning from both holistic and specific perspectives. Besides providing a summary picture of the lifelong learning situation in Canada, the CLI is meant to act as a gateway into the detailed set of indicators. In displaying the results by pillar of learning, peer group, the CLI makes it easy to highlight best practices, and identify priorities for action. The CLI allows for the setting of regional benchmarks for lifelong learning in Canada, and for further international comparisons of the underlying indicators of learning. Using this reporting framework, a community may easily see the strengths and deficits resulting in its unique CLI score and identify policy targets that would be most efficient in improving overall well-being in the community. At the same time, the CLI allows for comparisons with other indicators, such as indicators related to aspects of well-being. Good lifelong learning conditions, for example, show a high correlation to economic and social welfare.

A number of concrete conclusions are revealed from the 2007 Composite Learning Index, the analysis of the pillars of learning and the underlying indicators:

- Despite difficulties that emerged by combining data with different spatial resolution (e.g. some indicators were available at community level, others at regional level, etc.) and the conceptual complexity of bringing the range of issues that fall under the lifelong learning rubric into a single index, the CLI shows that lifelong learning performance can be tracked in rigorously and quantitatively.
- Comparisons of lifelong learning conditions at different spatial resolution (e.g. community, metropolitan area, city level) are facilitated by the CLI, which provides a useful way to identify best practices on an issue-by-issue and aggregate basis. Every community lags in performance on some issues. Each community has issues on which it can learn from the success of peer communities. Several communities mostly from Ontario, Saskatchewan and Alberta share a pie in the "best practices cake" of lifelong learning conditions.
- While substantial progress has been made in some communities on many issues and in most communities on some of the lifelong learning issues, there is still space for improvement in Canada, notably with regard to seven indicators: *participation in social clubs and organizations, volunteering, distance to vocational training, workplace training, high school drop out,* and *university attainment.* These indicators represent distinct and difficult policy challenges, as they are related to the individuals' behavior, except for the *distance to vocational training*. Here, the challenge of regional bodies is to create incentives to promote volunteering, and attract people's interest in completing high school and participating in university programs. At the same time, it is a responsibility of the local authorities to create vocational training (schools, business and secretarial schools) available at a close distance to the majority of the Canadian citizens.

- Canadian communities that have a high performance in the overall CLI have generally high performance in all four pillars of learning. The reverse, however, is not necessarily observed. The Leaning to Be pillar reveals a particular message: top CLI performance is achieved almost exclusively by communities with top performance in Learning to Be, because communities that are strong in Learning to Be are also strong in at least two more pillars of learning. This was not observed for any of the other three pillars of learning.
- Good lifelong learning conditions show a high correlation to economic and social welfare. In particular, the CLI scores are highly associated to the aggregate of six indicators: income, employability, population health, voters' participation, adult literacy and early childhood development, and to the individual indicator of adult literacy. Although correlation does not imply causality, and the latter cannot be tested in the Canadian dataset due to lack of timeseries, these results are consistent with the theory that lifelong learning translates into a more efficient use of an economy's human resources, in terms of employment, civil engagement, adult literacy and thus affects the overall productivity and economic performance in Canada. The high number of communities that was used for this analysis (n = 4576) supports further this argument.
- The average household income level and the lifelong learning conditions present a relatively good degree of linearity ($r^2 = 0.50$). A 10-point increase in the CLI score is associated with, on average, 10000 Canadian $ of extra annual income. Interestingly, for about 26 communities the CLI scores are very good (in the range 70-77), but the average annual income is the lowest in Canada (less than 35000 Canadian $). In those communities, which all belong to the Saskatchewan province, the very good lifelong learning conditions have resulted in very high adult literacy rates and very low unemployment rates, although the annual household income has remained at a low level. The widest spread of CLI scores is observed at annual household income of 53000 Canadian $. Communities at this income level score from as low as 53 to as high as 88 in the CLI. The communities with CLI scores close to 53 have not succeeded socially, as opposed to the communities with a CLI score close to 88 that have achieved both economic and social welfare. These results provide a further proof that the lifelong learning conditions in Canada, as measured by the CLI, go beyond income benefits, and capture other aspects of the quality of life related to social benefits.
- Population density is not a destiny in lifelong learning given that the correlation between the CLI scores and the population density across the 4576 Canadian communities appears to be random.

- There is a high degree of linearity between the CLI scores and the percentile rank score for the Canadian communities (slightly lower correlation is observed at the two very-ends of the distribution). A 5-point increase in the CLI score implies creating better lifelong learning conditions than 15% more communities compared to the situation before the improvement. This change will be less evident if a community is at the very-low or very high end in the CLI ladder.
- A scissors pattern (between CLI scores and variability in the indicators) is evident in the lifelong learning situation in Canadian communities, though not pronounced. Reducing even further the variability in the indicators should be among the objectives of lifelong learning policies and strategies in Canada. To be successful, a Canadian community must put simultaneous thrust on multiple goals within a coherent lifelong learning strategy, while emphasizing reduction of the existing gaps in areas where performance is lagging. As the exceptional behaviour of a few communities indicates, a disproportionate emphasis on a limited number of objectives without concomitant focus on many of the determinants of lifelong learning can yield only marginal results.

The Canadian Composite Learning Index is the first composite indicator in the field and opens the way towards establishing an operational model of lifelong learning. Many of the conclusions on the lifelong learning conditions captured and highlighted by the CLI for Canada could very much be the case for Europe, but they have, somehow, to be measured first. The conceptual and methodological framework of the Canadian CLI have all the appealing and necessary features needed to render the Canadian Composite Learning Index a forerunner to a European counterpart.

If such an attempt is ever made for Europe, then a comparison between the Canadian reality and the European one may be approached by means of the CLI coefficient, presented in this study. The CLI coefficient is essentially an equivalent of the Gini coefficient, adjusted to measuring the dispersion of the lifelong learning in Canada. The age-distribution is another issue that needs to be included when benchmarking lifelong learning conditions. Both these issues indicate directions for future research that would be worth the effort.

ANNEX: Methodological boxes and additional information

Box 1. Details on the learning to Know pillar

Learning to Know Represents knowledge acquainted at school or similar (e.g. student skills, attendance in formal education, distance to learning institutions)	
Indicator	**Why it is important**
Youth literacy skills (scores obtained by 15-y in reading, mathematics, problem solving) Source: OECD Programme for International Student Assessment	Advanced literacy skills (e.g. literacy in reading, math and problem solving, are critical indicators of the preparedness of young Canadians for the workplace and further education. Youth literacy skills give young people the capacity for innovative thinking and the adaptability required in today's knowledge-based economy. People with high levels of literacy are more likely to be engaged in society and to the community they live in.
Participation in post secondary education (PSE) (% of 20-24y, enrolled in university, college, or trades program) Source: Statistics Canada, Labour Force Survey	Early adulthood is an ideal period to participate in formal education, since such a possibility may be reduced later in life due to both familial or financial reasons. Post-secondary participation during a person's early 20s not only provides valuable skills, but establishes critical learning habits that are important for personal and professional success throughout one's entire life.
University attainment (% 25-64y who have completed a university program) Source: Statistics Canada, Labour Force Survey	Research clearly shows that higher educational attainment results in a wide range of economic and social benefits for Canadians, their communities and the country as a whole. University attainment is an indicator of "human capital," or the skills and knowledge available in the local workforce.
Distance to learning institutions (average distance Canadians travel to learning institutions, such as elementary and secondary schools, colleges and universities) Source: Internal CCL calculations	Easy access to learning institutions and services is important for the social and economic well-being of communities and individuals. These institutions and services provide a wide range of formal and informal learning opportunities that may not be readily available everywhere. A 2002 study by Statistics Canada indicates that high-school graduates who live beyond commuting distance to a college or university are less likely to participate in those post-secondary institutions. This was especially the case for students from low-income families. A similar study from the United States indicates that students attained, on average, one year less schooling if they resided in a community where there was no college nearby.
High School Drop-out rate (% 20-24y who did not complete high school and are not attending school) Source: Statistics Canada, Labour Force Survey	High-school completion benefits individual Canadians and the country as a whole. Research shows that high-school graduates are more easily employable, can choose from a wider selection of jobs and earn higher wages than those who leave school before getting their diploma. Research also shows there are health benefits: high school graduates make fewer visits to physicians and are more aware of what it takes to live a healthy lifestyle.

Note: Table re-adjusted from information contained in "The 2007 Composite Learning Index" report.

Box 2. Details on the learning to Know pillar

Learning to Do Represents knowledge acquainted at work (e.g. job-related training, workplace training, distance to vocational training)	
Indicator	**Why it is important**
Job-related training participation rate (% of 25-64y who participate in any form of job-related training, either in or out of the workplace) Source: Statistics Canada, Survey of Labour and Income Dynamics	Research has shown that job-related training can contribute to the success of Canadian employers and employees. Recent evidence shows that employers can benefit from job-related training through increased labour productivity, while employees stand to gain through better job performance, higher wages and improved career opportunities.
Availability of workplace training (% of employers that offer any form of training for their employees, whether on the job or in a more structured classroom setting) Source: Statistics Canada's Workplace and Employee Survey	Workplace training has been shown to be an effective way for workers to improve and retain their job-related skills. The availability of such training is key to keeping Canada's workforce competitive with other countries around the world. The availability of training at work provides opportunities for Canadians to improve practical skills and work-related competencies that they may not otherwise be able to access outside of work.
Distance to vocational learning institutions (average distance to the nearest vocational schools, business and secretarial schools) Source: Internal CCL calculations	(see Box 1 on the distance to learning institutions)

Note: Table re-adjusted from information contained in "The 2007 Composite Learning Index" report.

Box 3. Details on the learning to Live pillar

Learning to Live Together Represents knowledge acquiated in the community (e.g. citizen involvement & engagement, distance to community services)	
Indicator	**Why it is important**
Charitable giving (% of households that report making a donation to charitable org.) Source: Statistics Canada, Survey of Household Spending	Civic awareness and community involvement are important elements of the Learning to Live Together pillar. Charitable giving is a key indicator of civic involvement, because it demonstrates that individuals are interested in and concerned with the needs of others. Charitable organizations offer volunteers a wealth of informal and non-formal learning opportunities that they may not have access to in other aspects of their lives. Charitable organizations also provide the infrastructure for productive social relationships and help generate new ideas and methods of solving problems. In many concrete ways, charitable donations provide aid to Canadians for a variety of health and social problems, as well as providing opportunities to continue to learn and participate as active citizens.
Volunteering (% of Canadians involved in unpaid activities within a group or an organization) Source: Statistics Canada, Survey of Giving, Volunteering and Participating	Volunteerism is another expression of Canadians supporting each other and the communities they live in. Volunteering strengthens the social fabric, builds concern for and understanding of others, and brings people together to work toward a common set of goals. In recognition of the importance of volunteering, the United Nations declared 2001 the International Year of the Volunteer. According to a UN statement, volunteering allows "individuals [to] exercise their rights and responsibilities as members of communities, while learning and growing throughout their lives, realizing their full human potential." Volunteering helps fortify community services used by children, the elderly and others. It also provides learning opportunities for the volunteers themselves, opening the way to new skills and wider social networks.
Distance to community institutions *(average distance Canadians travel to the nearest library, business, civic and social associations, religious organisations)* Source: Internal CCL calculations	(see Box 1 on the distance to learning institutions)
Participation in social clubs and organisations (% of households that reported spending on membership or contributions to social clubs, political and fraternal organizations, co-operatives, and alumni associations) Source: Statistics Canada, Survey of Household Spending	Canadians participate in a wide variety of organized groups every year, from fraternal organizations, such as the Kiwanis or Shriners, to hobby-based groups, university alumni organizations and political parties. Participation in such groups provides an opportunity to develop and grow social networks, build trust and learn to live with others. In addition, these groups foster learning by: enabling Canadians to pursue their interests and gain knowledge of a wide variety of subjects, including politics, culture and art, bringing Canadians together to complete common projects and pursue common goals, and motivating group members to form social connections outside of their family and work environments. Canadians' participation in social clubs and other organizations demonstrates their level of engagement with their communities.

Note: Table re-adjusted from information contained in "The 2007 Composite Learning Index" report.

Box 4. Details on the learning to BE pillar

Learning to Be Represents knowledge acquainted at home (e.g. exposure to media, use of cultural resources) resources)	
Indicator	**Why it is important**
Exposure to media (% of households reporting expenditure on reading material and internet service at home) Source: Statistics Canada, Survey of Household Spending	Mass media in all of its forms plays an ever-increasing role in the lives of Canadians. Exposure to different types of media—from traditional print publications to multi-media websites—provides individuals with a broader variety of information and, in the process, expands their potential learning opportunities. Research has shown that the proliferation of media at home offers benefits to citizens. For example, international studies have shown a positive relationship between internet usage and reading ability in Canadian teenagers.
Learning though sports (% of households that report expenditure on sports and recreation facilities) Source: Statistics Canada, Survey of Household Spending	Regular participation in sports and recreational activities offers individuals more than physical benefits. Research has shown that it also helps develop life skills citizens need to enjoy a fuller, more satisfying life, such as leadership ability, problem solving, communication skills and personal management skills. Participation in team sports also helps to cultivate self-discipline, creative decision-making skills and the ability to work with others. According to The Conference Board of Canada's 2004 National Household Survey on Participation in Sport, the vast majority of Canadians recognize sports as an important way to gain valuable life skills. Other studies have also demonstrated the positive effects of physical activity on student performance and academic achievement.
Learning through culture (% of households spending on cultural activities such as museum visits, music festivals and the performing arts) Source: Statistics Canada, Survey of Household Spending	Exposure to arts and culture has been shown to have a positive effect on personal development. Recent research suggests that engagement with cultural activities bolsters self-confidence, boosts self-esteem, and enhances creativity and communication skills. Other studies have shown that children in particular can benefit from exposure to the arts, through a strengthened sense of self and increased opportunity for creativity and personal reflection.
Broadband internet service Access (% of households with access to broadband internet services, including fixed wireless, digital subscriber line (DSL), or cable) Source: Industry Canada, Broadband Office	Broadband is recognized as fundamental part of the infrastructure that connects communities, organizations and individuals across Canada. Its current influence on Canadian society has been compared to the impact the introduction of radio and telephone networks had during the early part of the 20th century. Research has shown that broadband technologies can strengthen Canada's social foundations by improving access to health care and educational services, and by expanding opportunities for Canadians who are otherwise excluded from the mainstream. Access to broadband internet also fosters economic and social development, by helping Canadian communities provide opportunities for skills development and lifelong learning. Broadband access, for example, offers significant opportunities for remote and rural communities by providing a greater number of educational, training and distance learning opportunities not viable through slower dial-up connections.
Distance to cultural resources (average distance Canadians travel to the nearest museums and art galleries Source: Internal CCL calculations	(see Box 1 on the distance to learning institutions)

Box 5. Descriptive statistics of CLI indicators for Canadian communities

Pillar	Indicator	Mean	CV (%)	Max	Min
		(across 4576 communities)			
Learning to Know	Youth literacy skills (PISA score)	525.3	2.1	546.0	497.5
	PSE participation (%)	33.0	25.9	53.6	11.1
	University attainment (%)	19.6	30.2	39.8	9.9
	Distance to learning inst.(km)	9.1	9.9	11.9	7.1
	High school drop-out rate (%)	9.9	16.4	11.7	3.8
Learning to Do	Job-related training (%)	21.1	21.6	33.3	11.3
	Workplace training (%)	56.1	10.4	77.4	46.0
	Distance to vocational training (km)	10.4	10.1	11.9	7.8
Learning to Live Together	Charitable giving (%)	70.9	15.8	91.5	36.1
	Volunteering (%)	44.6	17.7	89.7	28.3
	Participation in social clubs, etc (%)	18.3	18.8	30.6	10.7
	Distance to Community Inst. (km)	9.1	10.5	11.9	7.1
Learning to Be	Exposure to media (%)	68.8	9.1	81.3	56.3
	Learning through sports (%)	40.7	21.3	59.5	22.3
	Learning through culture (%)	34.5	18.6	51.6	22.1
	Distance to cultural resources (km)	9.2	12.9	11.9	7.1
	Broadband internet access (%)	0.5	81.3	1.0	0.0

Box 6. List of Canadian provinces and metropolitan areas included in the study

Canadian provinces
Alberta
British Columbia
Manitoba
New Brunswick
Newfoundland and Labrador
Nova Scotia
Ontario
Prince Edward Island
Quebec
Saskatchewan

Canadian metropolitan areas (*n* =142)			
Abbotsford	Fort St. John	North Bay	Sorel-Tracy
Alma	Fredericton	Okotoks	Squamish
Amos	Granby	Orillia	St. Catharines - Niagara
Baie-Comeau	Grand Falls-Windsor	Oshawa	St. John's
Barrie	Grande Prairie	Ottawa - Gatineau	Stratford
Bathurst	Greater Sudbury / Grand	Owen Sound	Summerside
Bay Roberts	Sudbury	Parksville	Swift Current
Belleville	Guelph	Pembroke	Temiskaming Shores
Brandon	Halifax	Penticton	Terrace
Brantford	Hamilton	Petawawa	Thetford Mines
Brockville	Hawkesbury	Peterborough	Thompson
Brooks	Ingersoll	Port Alberni	Thunder Bay
Calgary	Joliette	Port Hope	Tillsonburg
Campbell River	Kamloops	Portage la Prairie	Timmins
Campbellton	Kawartha Lakes	Powell River	Toronto
Camrose	Kelowna	Prince Albert	Trois-Rivières
Canmore	Kenora	Prince George	Truro
Cape Breton	Kentville	Prince Rupert	Val-d'Or
Centre Wellington	Kingston	Québec	Vancouver
Charlottetown	Kitchener	Quesnel	Vernon
Chatham-Kent	Kitimat	Red Deer	Victoria
Chilliwack	La Tuque	Regina	Victoriaville
Cobourg	Lachute	Rimouski	Wetaskiwin
Cold Lake	Leamington	Rivière-du-Loup	Williams Lake
Collingwood	Lethbridge	Rouyn-Noranda	Windsor
Corner Brook	Lloydminster	Saguenay	Winnipeg
Cornwall	London	Saint John	Wood Buffalo
Courtenay	Matane	Saint-Georges	Woodstock
Cowansville	Medicine Hat	Saint-Hyacinthe	Yorkton
Cranbrook	Midland	Saint-Jean-sur-Richelieu	
Dawson Creek	Miramichi	Salaberry-de-Valleyfield	
Dolbeau-Mistassini	Moncton	Salmon Arm	
Drummondville	Montréal	Sarnia	
Duncan	Moose Jaw	Saskatoon	
Edmonton	Nanaimo	Sault Ste. Marie	
Edmundston	New Glasgow	Sept-Îles	
Elliot Lake	Norfolk	Shawinigan	
Estevan	North Battleford	Sherbrooke	

Box 7. PCA, FA, Regression Analysis and their role in CLI development and analysis

Principal component analysis (PCA) is a multivariate statistical approach that essentially identifies patterns inherent in a multivariate model with a view to reduce the dimensionality in a set of variables, and/or to transform interdependent variables into significant and independent ones (Manly, 1994; Dunteman, 1989). PCA summarizes a *p*-dimensional dataset into a smaller number, *q*, of dimensions while preserving the variation in the data to the maximum extent possible. The *q* new dimensions are constructed such that:

1. They are linear combinations of the original variables.
2. They are independent of each other.
3. Each dimension captures a successively smaller amount of the total variation in the data.

These features of PCA justify its use as a tool to investigate the relationships between the selected indicators of lifelong learning. The objective was to capture those features in the data that help better understand lifelong learning or to discover interesting new patterns among the relationships between the indicators of learning. The p original indicators, per pillar of learning, were combined into q linear combinations, which form the new principal components of the system. A linear combination $Z_i, i = 1,..., p$ of a standardized data vector, $X = (x_1, x_2,..., x_p)$ is defined as:

$$Z_1 = a_{11}x_1 + a_{12}x_2 + ... + a_{1p}x_p$$
$$Z_2 = a_{21}x_1 + a_{22}x_2 + ... + a_{2p}x_p$$
$$...$$
$$Z_p = a_{p1}x_1 + a_{p2}x_2 + ... + a_{pp}x_p$$

where $a_{11}^2 + a_{12}^2 + ... + a_{1p}^2 = 1$, $a_{21}^2 + a_{22}^2 + ... + a_{2p}^2 = 1$, etc. The coefficients α_{ij} are chosen so that the explained variance of the original data is maximized (i.e. the squared difference of the new variable values and their respective means is maximized in relation to the total variance of the untransformed data). The results for $a_{11}, a_{12},..a_{1p}$ determine the first principal component. The second principal component with coefficients $a_{21}, a_{22},..a_{2p}$ is then obtained analogously by maximizing the variance orthogonal to the direction of the first component, and so forth. Orthogonality of the principal components means that they are statistically independent so that any changes in one component do not impact the others. This is sometimes a desirable feature of composite indicators.

The consecutive process of maximizing residual variance implies that at every step less variance is remaining. Once it falls below a specified threshold, the procedure is stopped and no additional principal components are calculated. Several criteria exist to determine the threshold value. Several methods consider the eigenvalues of the data matrix. The eigenvalue, λ, is the value that solves the detrimental equation: $|R - \lambda I| = 0$, where R is the $(p \times p)$ correlation matrix calculated from standardised indicators for the $n = 4576$ Canadian communities and p indicators ($p = 5$ for the Learning to Know and Learning to Be pillars, $p = 4$ for the Learning to Live Together pillar, $p = 3$ for the Learning to Do pillar) and I is the identity matrix. This provides a *p*-th degree polynomial equation in λ and hence K roots. These roots are called eigenvalues of the correlation matrix R. Next λ is arranged in descending order of magnitude, as $\lambda_1 > \lambda_2 > ... > \lambda_p$. Corresponding to each value of λ, the matrix equation $(R - \lambda I)a = 0$ is solved for the $p \times 1$ eigenvectors a, subject to the condition that $a'a = 1$ (normalization condition).

Values of λ *less than 1* (Kaiser criterion) indicate that there is no gain to be expected from adding the principal component to the set of selected components and that the first components whose λ *is greater than 1* are sufficient to summarize the data.

Factor analysis (FA) is similar to PCA. It also aims at describing the set of p indicators $X = (x_1, x_2, ..., x_p)$ in terms of a smaller number of q factors, and highlight the relationship between these variables. However, whereas PCA simply is based on linear data combinations, FA is based on a rather special model that assumes that the data are composed of common and unique factors, and consequently, that the data variance can be decomposed into that accounted for by the common and the unique factors. The model is given by:

$$
\begin{aligned}
x_1 &= a_{11}F_1 + a_{12}F_2 + ... + a_{1q}F_q + \varepsilon_1 \\
x_2 &= a_{21}F_1 + a_{22}F_2 + ... + a_{2q}F_q + \varepsilon_2 \\
&... \\
x_p &= a_{p1}F_1 + a_{p2}F_2 + ... + a_{pq}F_q + \varepsilon_p
\end{aligned}
$$

As previously $x_i (i = 1,..., p)$ represents the original variables (but standardized with zero mean and unit variance); $a_{i1}, a_{i2}, ..a_{1p}$ are called factor loadings related to the variable x_i; $F_1, F_2, ..., F_q$ are the uncorrelated common factors, each with zero mean and unit variance; and $\varepsilon_1, \varepsilon_2, ..., \varepsilon_p$ are the specific factors assumed to be independently and identically distributed with zero mean. There are several approaches to deal with this FA model, e.g. communalities, maximum likelihood factors, centroid method, principal axis method, etc. The most common is the use of PCA to extract the first q principal components and consider them as factors and neglect the remaining. Principal components factor analysis is most preferred in the development of composite indicators, e.g., Product Market Regulation Index (Nicoletti et al., 2000), as it has the virtue of simplicity and ensures that the resulting factors account for a large part of the cross-community variance of the underlying indicators. In fact, in factor analysis the focus is set only on those indicators of lifelong learning that are potentially useful for explaining the cross-community variation in learning environments (indicators values that are similar across communities are of little interest and cannot possibly explain differences in overall performance). Thus, the factors are constructed without pre-empting the conclusions of the analysis, since analyst's beliefs are not considered.

Factor analysis was used during the CLI development to extract the common factors from the indicators per pillar of learning, and to extract a single common factor (Economic and Social Well-Being Index) from the six economic and social indicators of learning. After choosing the number of factors to keep, we applied rotation, a standard step that aims at performed to enhance the interpretability of the results (Darton, 1980). The sum of eigenvalues is not affected by rotation, but changing the axes, will alter the eigenvalues of particular factors and will change the factor loadings. There are various rotational strategies that have been proposed in the literature. The goal of all of these strategies is to obtain a clear pattern of loadings. However, different rotations imply different loadings, and thus different meanings of principal components - a problem some cite as a drawback to the method. The most common rotation method is the "varimax rotation" and the one used here.

A multivariate regression analysis model further served to identify the weights to be attached to the factors within each pillar of learning, so that the aggregate pillar score would have the highest possible association to the ESWBI. Such a linear regression model can tell us something about the 'linkages' between the factors and the ESWBI, but they deal only with linear correlation per se. It can, however, stimulate research into new forms of conceptual modeling. During the CLI development, the set of factors per pillar, $F_1, F_2, ..., F_q$ (q depends on the pillar) is combined on the one hand and the ESWBI (denoted as $\hat{Y}$ for the sake of notation here) on the other. A multiple regression model is then constructed to calculate the relative weights of the factors: $\hat{Y} = b_1 F_1 + ... + b_q F_q$, where b_1 to b_q are the standardized regression coefficients (weights) of the respective factors. Note that all factors and the ESWBI were standardized prior to the multivariate regression analysis.

Multivariate regression was applied to estimate each pillar aggregate. Finally, the four pillar aggregates were further transformed into four orthogonal principal components and multivariate analysis was applied once again, so that the overall CLI would bear the highest possible correlation to the ESWBI.

Box 8. Cluster Analysis and its role in CLI analysis

Cluster analysis refers to a rich suite of statistical classification methods used to determine similarities or dissimilarities of objects in large datasets (see Kaufman and Rousseeuw, 1990 for a broad introduction to this field). We used this technique to identify groupings of the 142 metropolitan areas in Canada according to the 17 indicators of learning. Within each cluster, metropolitan areas have a better basis for benchmarking their lifelong learning conditions and identifying best practices (thus setting short-term targets) because the members of the cluster are similar with respect to the data used to classify them and the differences across the groups are maximized.

In this context, the question of interest in carrying out a cluster analysis of the CLI indicators (without assuming a pillar structure, for the moment) is whether there are similarities among Canadian metropolitan areas in their lifelong learning conditions at the CLI level and with respect to the CLI pillars and underlying indicators.

There is no best method for cluster analysis and the results of cluster analyses are subject to interpretation. Therefore, we applied two different algorithms. Specifically, we explored the data structure using a non-parametric, distance-based agglomerative clustering algorithm known as Ward's method. A feature of agglomerative clustering is that it starts with as many individual clusters as there are metropolitan areas. It then successively combines metropolitan areas that are most similar to each other with respect to a quantitative similarity measure until all metropolitan areas are joined in a single cluster. The similarity measure decreases during this process, while the within-cluster dissimilarity increases as more and more metropolitan areas are added.

The trade-off lies therefore in choosing a similarity measure, or "pruning value," that yields both a relatively small number of clusters and a high level of similarity. We determine that four clusters yield a reasonable division between the metropolitan areas. After determining the number of clusters, we use the k means clustering method developed by Hartigan and Wong (1979) to determine cluster membership. K means is a non-hierarchical method that requires that the number of clusters, k, be specified upfront (hence the preliminary use of Ward's method) and then iteratively finds the disjoint partition of the objects into k homogeneous groups such that the sum of squares within the clusters is minimized. The algorithm converges in fewer than 10 iterations for the 17 indicators and the 142 metropolitan areas.

Box 9. Multi-criteria Analysis and its role in CLI analysis

The Composite Learning Index is based essentially on an additive (and linear) model. Some policy analysts challenge aggregations based on additive models, inter alia, because of the undesired, at times, property of compensability. Compensability refers to the existence of trade-offs, i.e. the possibility of offsetting a disadvantage on some indicators by a sufficiently large advantage on another indicator, whereas smaller advantages would not do the same. Thus a preference relation is non-compensatory if no trade-off occurs and is compensatory otherwise. The use of weights, to be attached to the indicators, with intensity of preference originates compensatory multi-criteria methods and gives the meaning of trade-offs to the weights. On the contrary, the use of weights with ordinal criterion scores originates non-compensatory aggregation procedures and gives the weights the meaning of importance coefficients (Keeney and Raiffa, 1976; Podinovskii, 1994). Vansnick (1990) showed that the two main approaches in multi-criteria decision theory i.e., the compensatory and non-compensatory ones can be directly derived from the seminal work of Borda (1784) and Condorcet (1785). Indeed, looking at social choice literature, one can realize that various ranking procedures used in multi-criterion methods have their origins in social choice.

To deal with the issue of eventual compensability among the CLI indicators values, we built five scenarios that employ a multicriteria method, proposed by Brand *et al.* 2007, and which is essentially a combination of the Borda and the Condorcet-Kemeny-Young-Levenglick approaches (Kemeny, 1959; Young and Levenglick, 1978). The main reason for choosing the Brand *et al.* algorithm is that it can deal with thousands of constituencies (metropolitan areas in our case), unlike the currently available non-compensatory of the Condorcet type. Specifically, the algorithm computes scores for a community i as follows:

$$Y_i = \sum_{j=1}^{17} (n_{ij} + \frac{k_{ij}}{2}) \cdot w_j \, , \; 1 \le i \le 4576 \, , \; 1 \le j \le 17$$

where

$n_{ij} \equiv$ number of Canadian communities that have weaker performance than community i relative to indicator j, $0 \le n_{ij} \le 4575$

$k_{ij} \equiv$ number of communities with equivalent performance to community i relative to indicator j, $0 \le k_{ij} \le 4575$

$w_j \equiv$ weight assigned to indicator j

In brief, when a community *a* performs better than a community *b* for a given indicator, then community *a* gets all the credit (= indicator's weight), whilst community *b* gets zero credit. In case two communities have equal values in a given indicator, the credit (weight) for that indicator is split equally between the two communities. This way, a community cannot "compensate" for a preponderance of weak performance in few indicators with a small number of exceptionally high values in few indicators. In other words, to attain a reasonably good score under this approach, a Canadian community must devote a reasonable amount of attention to the majority of indicators of learning. This is not true under additive models, which are fully compensatory.

This approach was applied either to calculate the pillar scores and then the final composite indicator scores, or to calculate the composite indicator scores when a pillar structure is not present.

Box 10. Data Envelopment Analysis and its role in CLI analysis

In absence of reliable information about the true weights to be attached to the 17 selected indicators of learning, we endogenously selected those area-specific weights that maximize the composite indicator score for a given metropolitan area ($n = 142$) using the Data Envelopment Analysis (DEA) method. This gives the following linear programming problem for each metropolitan area i:

$$Y_i = \max_{wij} \frac{\sum_{j=1}^{17} y_{ij} w_{ij}}{\max\limits_{y_c \in \{dataset\}} \sum_{j=1}^{17} y_{cj} w_{ij}} \qquad \text{(\textit{bounding constraint})}$$

Subject to

$$w_{ij} \geq 0 \qquad \text{(\textit{non-negativity constraint})}$$

where $j = 1,...,17$, $i = 1,...,142$

In this basic programming problem, the weights are non-negative and an area's score is between 0 (worst) and 1 (best). The DEA-based composite indicator meets the important property of 'units invariance', which makes the normalisation stage for the underlying indicators redundant.

The non-negativity restriction on the weights, however, allows for extreme scenarios. If a metropolitan area has a value in a given indicator that dominates the values of other metropolitan areas, this metropolitan area would always obtain a score of 1.0 even if it has very low values in many other indicators. Furthermore, it may lead to a situation where a large number of metropolitan areas score 1.0, rendering a further assessment impossible. Therefore, some additional constraints on the weights were introduced, as recommended by several DEA supporters (see Thanassoulis *et al*. (2004) for a survey). We preferred to attach restrictions on the shares (instead of the weights), because shares (i) do not depend on measurement units and (ii) directly reveal the contribution of an indicator to the composite indicator score (Cherchye et al., 2007). Formally, the j-th share for a metropolitan area i is given as the product $y_{ij} w_{ij}$. Clearly, the sum of the shares equals the CLI_i. In what follows, we focus on *share constraints* (for each sub-indicator *i*) of the type

$$L_i \leq \frac{y_{ij} w_{ij}}{\sum_{i=1}^{m} y_{ij} w_{ij}} \leq U_i \qquad \text{(\textit{share constraint})}$$

with L_i and U_i the respective lower and upper bounds (Wong and Beasley, 1990).

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Abstract

Lifelong learning is crucial to a country's continued competitiveness, prosperity and social cohesion and yet no country has had a means of gauging the extent of lifelong learning within its population. The Composite Leaning Index (CLI) developed by the Canadian Council on Learning (CCL) shows how this gap might be filled by assessing the state of lifelong learning over time, for individual communities and across Canada using the conceptual four-pillar framework of lifelong learning proposed by UNESCO's International Commission on Education for the Twenty-first Century.

This report aims at validating and critically assessing the methodological approach undertaken by the CCL to build the CLI. Our focus is on the robustness assessment of the index, with a view to identify whether certain methodological choices distort the messages provided by the CLI. Data-driven narratives on lifelong learning issues in Canada are also discussed in this report with a view to show directions of discussions and messages that stem from an index-based analysis of lifelong learning and are related to identifying weaknesses, proposing remedial actions, allowing for easy spatial and temporal comparisons (benchmarking), prioritizing areas in Canada of relatively low lifelong content, monitoring and evaluating policies effectiveness and ultimately funneling resources to provinces through, for example, multilateral and bilateral agreements between Canadian cities. The conceptual and methodological framework of the CLI bear the appealing and necessary features to render the Canadian Composite Learning Index a forerunner to a European counterpart.

The mission of the JRC is to provide customer-driven scientific and technical support for the conception, development, implementation and monitoring of EU policies. As a service of the European Commission, the JRC functions as a reference centre of science and technology for the Union. Close to the policy-making process, it serves the common interest of the Member States, while being independent of special interests, whether private or national.

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